

Topics on the Economic Outcomes of Young Adults

by

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Dissertation submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in the Department of Economics
in the Graduate School of Duke University
2013

ABSTRACT

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Abstract

In this dissertation, I present two essays linked by their focus on forces that act on young people as they prepare to enter adulthood and their economically independent life. In the first, I investigate the impact of parents' location and occupational attributes on young adult children's labor market outcomes, particularly wages. I exploit the genealogical structure of the Panel Study of Income Dynamics (PSID) to measure locations, occupations and wages of young adults and their parents. I find that college graduates who live near their parents have lower wages than those who do not, but that wages for high school graduates are not strongly correlated with proximity to parents. In order to determine the reasons for these patterns, I build and estimate a model of young adults' location and occupation decisions to account for potentially competing effects parents may have on their children's wages. Using the model, I find evidence that young adults have strong preferences for living near parents, a result which through compensating differentials can partially account for the tendency to earn lower wages when near parents. However, I estimate that young people across all levels of educational attainment place similar value on this proximity. I also find that living near parents may directly enhance productivity and/or occupation quality and lead to higher wages. In particular, I find that high school graduates whose fathers are in cognitive skill-intensive occupations have higher wages within an occupation and switch into more cognitive skill-intensive occupations themselves if they live in the same labor market as their father, but that this effect

is not present for college graduates. I also find a differential selection in the earnings potential of movers and differential impacts of the cost of occupational switching between high school and college graduates. These differences all substantially contribute to the differences in wage and location choice patterns between high school and college graduates.

In the second, I present joint work with V. Joseph Hotz, Peter Arcidiacono and Esteban Aucejo on college admissions in the University of California system. College graduation is an important outcome for future welfare, and in this chapter we examine possible causes for an increase in college graduations among UC students who enrolled in 1998-2000 versus those who had enrolled in the previous three years. In between these cohorts, Proposition 209 banned using racial preferences in admissions at California's public colleges. We analyze unique data for all applicants and enrollees within the University of California (UC) system before and after Prop 209. After Prop 209, graduation rates of minorities increased by 4.4%. We characterize conditions required for better matching of students to campuses to account for this increase. We find that Prop 209 did improve matching and this improvement was important for the graduation gains experienced by less-prepared students. At the same time, better matching only explains about 20% of the overall graduation rate increase. Changes after Prop 209 in the selectivity of enrolled students explains 34-50% of the increase. Finally, it appears UC campuses responded to Prop 209 by doing more to help retain and graduate its students, which explains between 30-46% of the post-Prop 209 improvement in the graduation rate of minorities.

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1

Introduction

The body of this dissertation consists of two separate essays about economic outcomes of young adults. In the first, I analyze the evolution of young men's wages, occupations, and location decisions from the the beginning of adulthood into their mid-thirties. I am particularly interested in the effects parents have on their sons' decisions and how those effects differ by characteristics of both parents and sons. First, I establish correlations in data from the PSID that high school graduates who live in the same Metropolitan Statistical Area (MSA) as their parents tend to have slightly higher wages than those who do not, but college graduates in the same MSA as their parents tend to have lower wages. I hypothesize that these effects are a combination of a preference to live near parents, which would cause accepted wages near parents to be lower than otherwise, and a network effect parents may have on their young adult children in the local labor market, which would have a positive effect. Both of these effects have a basis in the economic literature, but it is uncommon for both to be encompassed in one model. I set forth a model to investigate these relative value of these effects and their contribution to wages and occupations for young men in each education group.

I find that both high school and college graduates place large non-monetary value on living near parents. Furthermore, I find that high school graduates whose fathers have occupations requiring high cognitive skill tend to receive higher wages and move into more cognitive skill-intense occupations themselves when living near those fathers, but this effect does not exist for college graduates. I find that this difference, along with costs of switching occupations and differential selection of movers, help explain the different wage patterns by location for high school and college graduates.

In that essay, I begin my analysis after education has been completed. While I am making a comparison across education groups, which is an important element of my study, I am taking as given an individual's educational achievement. The second essay, in contrast, focuses on college students' outcomes and takes college graduation as the specific outcome of interest. In this chapter, my co-authors V. Joseph Hotz, Peter Arcidiacono, Esteban Aucejo and I examine graduation rates at University of California (UC) campuses for the 1995-2000 entering classes. During this time period, California passed Proposition 209, banning the use of race in admissions decisions. After Prop 209, graduation rates of minorities increased by 4.4%. Using data for all applicants and enrollees within the University of California (UC) system before and after Prop 209, we examine the reasons for this gain. Because we have information on all eight UC campuses from this time period, with each student's application, admission and matriculation decisions by campus, we are able to test the *mismatch hypothesis*, which suggests that affirmative action may place minority students in universities that do not provide them with the highest probability of succeeding (by our measure, graduating within five years). We characterize conditions required for better matching of students to campuses to account for this increase and present evidence that different UC campuses have a comparative advantage at graduating students at differing levels of academic preparation, meaning that mismatch is a theoretical possibility. In practice, we find that Prop 209 did

improve matching and this improvement was important for the graduation gains experienced by less-prepared students. However, better matching only explains about 20% of the overall graduation rate increase, and does not explain graduation gains that were seen among highly prepared students, for whom matching did not greatly affect graduation outcomes after Prop 209. We find that after Prop 209, there was an increase in the average preparation of minority students who ultimately enrolled at UC campuses, and the changes in selectivity of students explain 34-50% of the increase. Finally, it appears UC campuses responded to Prop 209 by doing more to help retain and graduate its students, which explains the remaining post-Prop 209 improvement in the graduation rate of minorities.

Parental Influence on Labor Market Outcomes and Location Decisions of Young Workers

2.1 Introduction

It is well known that parents play a large role in shaping all kinds of their children's later life outcomes. There has been extensive research on human capital development of children, in which parents are known to play a large role¹. There is less study and certainly less consensus on the direct effects parents have on adult children. It is precisely because of the all-encompassing nature of parental involvement that it can be difficult to determine the full set of mechanisms by which parents affect their grown children. In addition to the parental investment in their children in earlier years, parents and children naturally tend to be similar in many observable and unobservable ways. In this paper, I look at parental influences on children's wages that can be attributed directly to contemporaneous factors when parents and adult children live near one another, taking childhood investments and other transmission of human capital before coming of age as given. I am interested in what

¹ For instance, Heckman (1999) and Almond and Currie (2011) are two of many works by these and other co-authors concerning early development of human capital

types of effects living near parents may have, and in particular whether these effects are different for different types of people.

In the United States, many young people continue to live in the same city where they grew up and where their parents still live even after establishing their own household. Using state-level data from the last three decades, Malloy et al. (2011) document that annual interstate move rates are around 4 percent for young adults and that over two-thirds of the US population lives in the same state where they were born. I show similar patterns from the Panel Study of Income Dynamics in Table 2.1, which I will discuss further in the next section of the paper. The propensity to live near is partially due to the relative scarcity of long-distance moves, but even a substantial percentage of those who do move away eventually come back. One common explanation is that this represents a tension between family and labor market factors: a young person may move away early in their career and settle down back home later in life. However, there is also an economic literature on the value of informal networks in the labor market. In this case, there is no tension between these factors: low mobility could be explained by the desire to stay in the home network, especially if there were also preference-based reasons to stay.

I am interested in measuring the how the value of parents to adult children manifests in these two potentially competing effects. Family ties between children and parents may cause children to accept lower wages in order to live near their parents than they could earn if they were willing to move across locations. On the other hand, parents may help children find better jobs than they would be able to get otherwise if they live in the same location. Therefore, since there are factors working in each direction, proximity to parents has an ambiguous effect on adult children's wages. Indeed, I note that in the unadjusted data, high school graduates in the same location as their parents tend to have somewhat higher wages as those in other locations, but college graduates' wages are significantly lower when in the same

location as parents. My goal in the paper is to formulate and estimate a model that can separately identify different channels through which parents can affect children's wages, and use the model to shed light on the relative importance of these channels and how their effects differ by education to produce the result that I find in the unadjusted data.

In order to determine the relative importance of these effects, I will use the Panel Study of Income Dynamics (PSID) and build a dynamic structural model drawing from literatures in internal migration, occupational choice and intergenerational transmission of economic variables. Using the model, I find that young men of any educational background place large utility values on living near parents and that high school graduates have significant wage benefits from locating near fathers who work in occupations requiring high cognitive ability.

Finally, I examine wages and migration rates under various counterfactual scenarios to determine the relative importance of the channels in my model and how they inform the differential results I find by education. The beneficial effect of fathers in high cognitive occupations mentioned in the previous paragraph is only one reason high school and college graduates' wage patterns differ by proximity to parents. I also find that college-educated "location movers" are more likely to be of relatively high ability compared to "location stayers" than high school location movers, and that lower occupation switching costs for high school graduates also make living near parents more beneficial. Separately, I also show that the utility value of living near parents causes move rates to be only about two-thirds of what it would be in the absence of any preference for family.

The paper is organized as follows. In Section 2.2, I provide more background on what is known from the literature about internal migration, wages, and family factors, as well as intergenerational correlations of occupation and other economic outcomes. In Section 2.3, I explain my dataset and provide descriptive evidence that

parental characteristics have different patterns of influence on their sons' outcomes depending on where they live in relation to one another. In Section 2.4, I lay out my structural model of sons' decisions and discuss estimation and identification of that model in Section 2.5. In Section 2.6, I present my main results. Section 2.7 concludes and discusses future and ongoing work.

2.2 Background

2.2.1 Reasons for Migration

Internal migration is a notable feature of the United States labor market. As such, it has received extensive attention in the economic literature². Existing theory places the migration decision in a utility-maximizing framework. Individuals choose the locations that offers the best combination of labor market opportunities and amenities, with family and social ties being a key non-market amenity in the origin location. There are many examples in the literature examining each side of this issue. In a series of papers in the early 1990s, Borjas and co-authors examine internal migration as an investment by which workers, especially young workers, move to areas with greater returns for their skills,³ and this general framework studying a single move characterized a number of subsequent papers. More recently, Kennan and Walker (2011) apply new modeling techniques to dynamically model a full sequence of location decisions of high school graduates. In the model, young workers are driven by income maximization, moving both to gain access to locations with higher mean wages than their origin or to improve their job match quality if they have a bad realization in their current location. The model also includes large moving costs which are subject to idiosyncratic shocks, meaning agents also wait to move when they face favorable shocks. This framework, in which individuals decide whether or

² Much of the seminal migration literature is summarized in Greenwood (1997)

³ In particular, see Borjas, Bronars and Trejo (1992a, 1992b)

not to move every period and account for the possibility of future moves, is what I will use to build my own model. With a slightly different focus, Basker (2002) models differing incentives to local or global job search by education as a key reason for differences in migration rates. Responsiveness to migration incentives by education is also a primary focus of Wozniak (2010). These papers provide some of the impetus for me to estimate my model for high school and college graduates, in order to test possible reasons for the difference in migration rates by education in the context of my model.

The literature on the family side of the issue largely stems from Mincer (1978), who directly analyzes the effects of family ties on migration, employment and earnings outcomes. These studies most often focus on intra-household decision-making, in which migration can have differing payoffs to spouses. In cases where one spouse would be made better off by moving but the other would be better off staying, the need for optimization at the household level results in joint location constraints ⁴ or even marital instability ⁵. Cooke (2008), writing in a cross-disciplinary review of migration research, makes the point that family relationships besides marriages can induce similar tensions between family and income maximization, writing that “given the growing awareness of how the migrations of adult children and their parents are affected by events in each other’s lives...a broader view of family migration encompasses not only the migration of a family, but individual migration events that are made within the context of a family.”

This relationship between parents and adult children has considerably different features than the more commonly studied relationship between spouses within a

⁴ Costa and Kahn (2000) and Compton and Pollak (2007) look at this issue for college-educated couples but reach different conclusions as to whether the location is based primarily on optimal joint employment concerns or for mainly the husband’s

⁵ Gemicci (2008) models married individuals receiving job offers across geographic regions and finds effects on divorce rates and the gender wage gap

household. Spouses make decisions and move together, and as the above papers show, migration events made for one spouse’s career are very likely to be disruptive to the other’s. Parents are not joint decision makers with their adult children in the same way, but as Cooke suggests, they may still affect their children’s migration decisions. Indeed, this is the focus of papers such as Konrad et al. (2002), in which elder siblings move away from home to tip responsibility for parent care toward their younger siblings, and Loken et al. (2011), which finds that married couples in Norway tend to live closer to the husband’s parents than the wife’s. These papers focus on the location choices of young adults with respect to their parents for non-labor market reasons. However, one very important point that is not a key point of emphasis in these papers is that unlike spousal effects, in which the “trailing spouse” may have to sacrifice job attributes for the sake of the “leading spouse’s” career, adult children may in fact benefit from staying near their parents and having access to their resources, information, or networks. In my analysis, I want to determine how much of the observed tendency for parents and adult children to live near each other is due to labor market benefits versus other utility factors.

2.2.2 Parents and Adult Children

In order to look more carefully at the relationship between parents and adult children, I will also draw on the economic literature on intergenerational correlations between parents and children. In a Handbook of Labor Economics chapter, Black and Devereux (2011) give a useful overview on recent literature on intergenerational linkages. A common starting point is measuring the intergenerational elasticity of permanent earnings, but many papers extend their analysis either by measuring transmission of other characteristics such as education, occupation, or IQ, by attempting to identify causal effects of parental characteristics on child outcomes, or both. To study labor market outcomes, I will follow many researchers by placing

particular focus on the links between fathers and sons, although I will also use some maternal characteristics in my analysis.

The most important intergenerational characteristic for my purposes is occupation. This can be measured either by calculating the incidence of fathers and sons sharing the same occupation (at a specified level of precision) or alternatively by measuring correlations along a continuous measure of occupation. Using either method, occupation is consistently found to be highly correlated across generations. I will consider both alternatives, measuring occupation at the one and three-digit level.

Separately, in much of my analysis, including the structural model, I use a continuous mapping of three-digit occupations into a “cognitive” and “motor” task intensity space developed in Yamaguchi (2012). In this paper, Yamaguchi uses the Dictionary of Occupational Titles to determine the level of cognitive and motor skills demanded by each three-digit occupation and then ranks each occupation by task intensity in each dimension. He then standardizes them into percentiles (using number of workers) and normalizes these percentiles of intensities onto a $[0,1]$ scale, translating three-digit occupations to cognitive-motor pairs on $[0,1] \times [0,1]$. In this paper, he is interested in tracing how workers choose among occupations and develop their own skill-specific human capital in order to maximize their long-run welfare in the labor market. I will use the measure somewhat differently. For my purposes, it is valuable to have a continuous index of occupations to measure transmission of occupation on more than a binary scale of whether sons enter fathers’ occupations, and I prefer this mapping of occupations into a two-dimensional space to using a one-dimensional occupational prestige index because I want to see whether a sons benefit from having a father with a “good” occupation, but also whether they benefit when in a similar occupation whatever its characteristics. An example of the former case is a father in an executive or managerial position who is able to use his connections to get his son an entry-level position of any type, whereas the latter case

would be consistent with a situation in which a son looking for an office job benefits from a father in a white-collar occupation himself, but a son looking for a blue-collar job may benefit more from a father who works in a factory or on a construction crew. I am not interested in modeling directed occupation search or skill formation, but rather focus on intergenerational relationships in occupation and how agents' occupation characteristics interact with a permanent ability to produce returns in the labor market. At all points, it is important to keep in mind the task intensities represent characteristics of an individual's - whether father or son - occupation, and not of the individual himself. With this in mind, I will introduce the following notation. Using the Yamaguchi measure, each occupation j has cognitive and motor task intensities $[cog(j_{it}), mot(j_{it})]$. If individual i works in occupation j at time t , I will use the notation $cog(j_{it})$ for the task intensity of his occupation, where task intensity is a function only of an occupation, and j_{it} denotes that i has occupation j at time t .

One crucial yet difficult question in the literature is that even if there is a correlation between father's occupation and son's outcomes, which I will show that there is using my adaptation of the Yamaguchi measures, it may still be difficult to determine the mechanisms of this correlation. Sons may end up in similar occupations to their fathers because those fathers help them find similar jobs, because they have naturally similar skill sets, or because the sons are exposed to father's occupation and learn more about it. There are numerous efforts to shed light on some aspect of these mechanisms. One strategy is to investigate the incidence of fathers and sons working for the same employer, which can be evidence of fathers using their connections on their children's behalf. Corak and Piraino (2010) find the incidence of employment at the same firm is common in Canada, especially for high earners. Kramarz and Skans (2007) find that Swedish sons are more likely than their classmates with similar skills to get a job at their father's plant, although in contrast

this finding applies mostly to low-educated workers. Hellerstein and Morrill (2011) use comparisons in probabilities that children (particularly daughters) enter their fathers' versus fathers-in-law's occupations to shed light on parental investments in children, modeling the difference between the two as a measure of transmission of occupation-specific human capital.

2.2.3 Parents' Effects on Wages

I am interested in whether fathers affect sons' wages through two primary channels: first, whether they act as a "family tie" and depress wages by limiting mobility, such as seen in the mostly spouse-based migration literature growing out of Mincer, and second, whether they affect occupation or earnings through direct labor market intervention, as is considered in the intergenerational correlation in earnings literature. I will also have to account for observed and unobserved similarities between parents and children. One strategy used in several studies of intergenerational elasticity of earnings is to try to decompose the effect on earnings by a two-step process, determining the effects of parents on intermediate outcomes and then the effects those outcomes have on wages, for instance Gintis and Bowles (2002). However, to my knowledge few if any of these studies track the relative locations of parents and adult children and interact that with characteristics. This is a primary focus of what I will do. I will think of proximity to parents both as a possible compensating differential, in which case it will have a negative effect on wages, and also as a potential source of opportunity in the labor market, in which case it may have a positive effect. First, I will present correlations and regressions uncorrected for any type of selectivity to establish the patterns in the data, and then I will develop a model that will incorporate unobserved ability that may differ between migrants and non-migrants and different education or occupation groups.

2.3 Descriptive Statistics and Regressions

2.3.1 Data Description

I build my dataset using white male PSID respondents aged 18-35. I posit that younger men are more likely to require help from parents or other social networks both in the labor market and for resource sharing or other informal or social help outside the labor market. Additionally, parents of individuals in this age group are typically working age themselves or very recently retired, meaning resource flows ought to primarily go from parents to children. In later years, when parents are retired and may face health issues while their adult children are more established, the direction of care may be a much different issue. I choose to focus on men because career-based location decisions of young couples are typically made for the sake of the husband’s career ⁶, which means that young men’s decisions are the most likely to be made for own income or family reasons, as opposed to the spouse’s income. I limit the sample to whites, the largest ethnic group in the PSID and US population, in order to abstract from potential cultural differences across groups.⁷ Further, I cut the sample to “second-generation” PSID respondents. By this, I mean I use only the children of original 1968 PSID heads and wives. The advantage of this subsample is that they are the only group for whom both mother and father are endowed with the “PSID gene.” Only individuals with the PSID gene are guaranteed to be followed across all PSID waves regardless of other household composition. By using second-generation individuals, I should thus observe location and other information for both parents regardless of which PSID following rules are in effect for a given year, the individual’s age or his parents’ marital status. Even in areas in which I

⁶ Compton and Pollack show this is true even for “power couples” in which both couples have high education

⁷ Kennan and Walker make a similar data cut, as does Bishop. Both of these studies further limit their sample to high school-educated men.

only require father’s information, this is valuable because I know that all fathers of second-generation respondents will have the PSID gene.

I then clean the data and generate variables to create the analysis sample. I take each of my sample member’s age, income and hours worked, three-digit occupation, educational achievement, US state of residence, and household headship status directly from survey data. I also use linking information to find whether the agent’s mother and father are respondents in that year of the data, and if so what their employment, occupation, and state of residence are. I also know whether the parent and child live in the same household. I use the sample years 1976-1993 because that is a relatively consistent period of sample data collection, as well as because many second-generation PSID respondents came of age during this time period.

One key limitation of the PSID, for my purposes, is that while income and hours worked are available for all respondents, occupation is usually only reported for the male and female heads of household. This means that occupation decisions of individuals who live with their parents, but are working, cannot be measured as it can for individuals living independently.

For all types of occupations, I measure wage hourly by taking reported annual income and dividing by hours worked. After 1990, labor and asset income are measured separately, and I use labor income to determine wage. Before 1990, all income is reported together (although whether an individual had any asset income is asked). In the earlier waves, I use an imputation to estimate labor income for those who report having both types of income⁸. In order to limit the effect of outliers, I enforce that all wage rates must be between \$1 and \$100 per hour in 2007 dollars.

I also fix individuals’ education and home location over time. For every observa-

⁸ I use the newer waves to estimate what proportion of income is asset income, controlling for education and other individual characteristics, and assume this function holds for the older waves. Since this is a young sample, most individuals do not report any asset income, leading me to believe this does not meaningfully affect my analysis

tion, I make the individual’s home location the location (measured alternatively at the US state or MSA level) at age 17. If the location is unavailable for any reason, I go back one year at a time until I have a non-missing entry. For education, I record the highest educational level ever achieved. For analysis purposes, I use this to divide the population into four education groups: those with less than a high school degree, those with a high school degree but no college, those with some but less than four years of college education, and those with a bachelor’s or graduate degree. In the primary analysis, I will use the education groups with the most observations: high school graduates with no college education, and college degree holders.

I also make use of the restricted-access PSID Geocode data, in which individuals’ location is more precisely measured than what is available in the public data. In the analysis, I use Metropolitan Statistical Area (MSA) as an alternative to state. For the purposes of the descriptive regressions, using MSA serves as a robustness check to state in determining whether parents and children are in the “same location.” If necessary, I can be even more precise; the Geocode data allows for a determination by county or zip code, which can be used to approximate actual distance between households or across moves. I choose MSA as my primary unit of measurement because it is a good approximation of a city and labor market. I expect parents to affect children most when they share a labor market, and an MSA also closely approximates a same-day driveable distance which would be important if preferences for living near parents has to do with proximity, as would be necessary for child care or for sharing meals, storage space or other household resources.⁹ Respondents in rural areas are grouped into non-MSA regions for labor market purposes.

⁹ One possible extension for future work is to use the Geocode data to measure within-city distance, which could have an especially strong effect on resource sharing, but in this paper I will only use MSA-level data.

2.3.2 Geographic Mobility

The most important fact about place of residence is also the most basic: most young people live near where they grew up. This is true for all education groups, although the effect is weaker as education increases. When I define a home MSA, as in Table 2.1¹⁰, I see fewer individuals remaining at home than state-level analyses but the relative patterns by age and education are similar. The 18-23 year old group is the least different, but among 24-29 and 30-35 year olds the likelihood of being at home is 10-15 percentage points lower. College graduates over 30 are more likely to be outside their home MSA than in it (39.6%), the only group for whom that holds.

As a corollary to the statistics on home location, there is a difference in annual inter-MSA move rates across education. As seen in Table 2.2, these rates are most dissimilar among the 24-29 and 30-35 age groups, after college graduates have completed school. For 24-29 year olds, annual inter-MSA move rates reach nearly 15% for college graduates and 8-10% for the other groups, with a corresponding 9.3% and 4-6% for 30-35 year olds.

Both the home location and move statistics calculated in the tables are determined from each person-year observation in the data. In order to get a balanced cross-section, I look at total moves made by age 30, as well as the proportion of individuals that have made at least one move by that age. Over half of college graduates have moved across MSAs by 30, as have about one-third of others. Movers are divided roughly by thirds as to whether they have made one, two, or more than two moves. Total moves per mover tends to rise with education, although high school graduates are more likely to have made three or more moves than those with some college (but no four-year degree). These results are presented in Table 2.3.

¹⁰ In the appendix, I report the following tables by state instead of MSA to facilitate comparison to Greenwood and Malloy. My sample shows similar migration rates to those found by these authors using CPS or Census data.

The data on move rates is consistent with what Malloy et al. and others have found using larger national datasets. While long-distance moves are relatively low probability events annually, they are still important since many young workers make them at some point and due to the infrequency of moving, each move is likely to have lasting effects. It is also noteworthy that moves are more common when using MSA-level data such as I have from the Geocode information than when using state data.

2.3.3 Intergenerational Correlations

In the background section of the paper, I discussed some of the economic literature about internal migration and about intergenerational correlations of various characteristics. In this section, I note the basic structure of intergenerational correlations in my data and confirm that it is similar to what has been found previously, as I have done in the last section for the mobility statistics.

First, I look at the simplest form of intergenerational transmission to measure: education. Not surprisingly, fathers and sons tend to get similar levels of education. As shown in Table 2.4, 22% of sons of high school dropouts become dropouts themselves, whereas sons of high school graduates drop out at 6% and sons of college graduates just under 1%. Nearly 60% of sons of college graduates obtain four-year degrees themselves, more than twice the rate of sons of high school graduates or those with some college. Children of fathers with some college are more likely to get some college than those of high school graduates, although the proportion getting four-year degrees is similar between those groups. This is a result noted by Black et al (2005) and Ermisch and Francesconi (2001), among others. If I treat my education groups as a continuous instead of a categorical variable, taking values of 0 through 3 for increasing levels of education in the four groups I define, I obtain a correlation coefficient of 0.43, similar to what is found in the intergenerational correlations

literature.

When looking at similarity by one-digit occupation, many sons are in different professions from their fathers. “Professional work” is the most commonly transferred, with about half of sons of professional workers becoming professional workers themselves, but that category is fairly broad and mostly driven by the transmission of college education. Overall, around 25% of sons are in the same one-digit occupation as their fathers, a result close to that found by Hellerstein and Morrill.

By their continuous nature, the Yamaguchi measures allow for a closer look at occupational similarity beyond only measuring whether sons go into the same careers as their fathers. As displayed in Table 2.5, the correlation of cognitive task intensity of father’s and sons’ occupation in the same period is 0.58. The correlation of father’s and sons’ motor task intensity is 0.48. These results are both fairly stable by sons’ or fathers’ education levels. Focusing on the son’s occupation task intensities, cognitive and motor intensities are negatively correlated (-0.19).

Finally, I run regressions with the son’s occupational cognitive task intensity as the dependent variable, with measures of father’s occupation and location among the explanatory variables. These regressions are designed to test how well father’s occupation correlates with son’s once other controls are included, and, more directly pertinent to my analysis, whether these correlations are affected by the father and son’s relative locations. I focus primarily on an occupation’s cognitive rather than motor intensity because, as I will show later, occupational cognitive intensity consistently correlates with higher wages where motor intensity does not. I use the following OLS specification:

$$\begin{aligned}
cog(j_{it}) = & \gamma_1 I_t[L_{it}^f = \ell] + \gamma_2 mot(j_{it}) + I_t[L_{it}^f \neq \ell] * (\gamma_3 cog(j_{it}^f) + \gamma_4 mot(j_{it}^f)) \\
& + I_t[L_{it}^f = \ell] * (\gamma_5 cog(j_{it}^f) + \gamma_6 mot(j_{it}^f)) + \lambda Z_{it} + \mu_{it}
\end{aligned} \tag{2.1}$$

In this regression and the wage regressions to follow, i indicates the individual, l individual's location, t calendar year, X years of experience, and $I_t[L_{it}^f = \ell]$ is an indicator function for whether the individual resides in the father's location. The cognitive and motor task intensity of the individual's occupation j at time t is denoted $cog(j_{it})$ and $mot(j_{it})$, and task intensities of the father's time t occupation are $cog(j_{it}^f)$ and $mot(j_{it}^f)$. In this particular formula, Z_{it} stands for a set of controls including age, marital and fertility status and father's education. In these regressions, I will stratify by education of the individual.

The results from this equation, shown in Table 2.6, establish that father's occupation and location does play a role in task intensities. Individuals in the same location as their fathers tend to be working in occupations with lower task intensities, but the result is small or zero in most cases. The father's occupation's cognitive intensity is strongly positively correlated with the son's occupation's cognitive intensity for all education groups, and this effect is larger when father and son are in the same state or MSA. Motor intensity of occupations is less important but typically has the opposite relative effect.

Even establishing a correlation between father and son's occupations' task intensity still leaves open the question of why this relationship exists. I will attempt to address this question in the model, but the descriptive regressions do not distinguish between any number of possible reasons. It may be this correlation reflects common ability or interests between fathers and sons that leads them to enter similar occupations. If so, this commonality could itself have multiple possible causes. It could come either through genetics or else be a product of the environment, in which a young son observes his father's occupation, learns about it and that familiarity leads him to enter a similar occupation himself upon reaching adulthood. It could also be the father has contacts within his own occupation or similar occupations to help find his son employment in certain occupations. The reason behind the result that

cognitive task intensity is more strongly correlated between father and son's occupation when they share a location also cannot be pinned down by these regressions. Sons who choose to remain near fathers may be more similar than those who do not, or they may face more similar job opportunities, or they may be more likely to have fathers intercede for them directly in the labor market. The regression in Table 2.6 only suffices to establish intergenerational correlation in occupation task intensities; in the model section, I will discuss ways in which I make efforts to distinguish these possible explanations and also denote where the model will not be able to make these distinctions. Making these distinctions is important because different potential mechanisms underlying intergenerational correlations in occupation have different implications for how parents affect their sons' labor market opportunities and therefore how sons make location decisions.

2.3.4 Mobility and Wages

Since moving is a costly process, it may not be surprising that moves are rare. The necessary economic question of interest is what benefits are agents attempting to gain by moving, and the most standard answer is that there may be wage benefits to searching a national labor market. To see whether this is supported in the raw data, I first simply determine mean wages by education and location. These results are in Table 2.7. For college graduates, individuals living in the same location as their fathers have lower wages than those who live in a different location as their fathers. However, high school graduates are more likely to live near their fathers and, more strikingly, do not have lower wages for the subgroup near their fathers. I examine these correlations further by using wage regressions to see how these correlations are affected by other characteristics.

This set of wage regressions are described in Table 2.8 of the paper. The overall purpose of these regressions is not to attempt to establish a causal relationship but

instead to motivate the structural model. When accounting for more covariates in a simple way, the correlations in Table 2.7 appear to hold up and other interesting correlations emerge: I find that occupational attributes of the father correlate more strongly with wages of sons when the two live in the same labor market. During the rest of this section, I will use the descriptive regressions to highlight these correlations, and then in the next section I will write down a model to attempt to determine the reasons for the patterns seen here.

In that spirit, I begin by running the following wage regression separately by education group:

$$\ln w_{ijlt} = \beta_{0l} + \beta_{0j} + \beta_{0t} + \beta_1 X_{it} + \beta_2 X_{it}^2 + \beta_3 I_t[L_{it}^f = \ell] + \nu_{ijlt} \quad (2.2)$$

These regressions are subscripted as in the previous section, with X_{it} indicating years of experience at time t , β_{0l} , β_{0j} and β_{0t} indicating vectors of dummy variables for location, one-digit occupation and calendar year, and $I_t[L_{it}^f = \ell]$ an indicator for whether the individual's father is located in the same location ℓ as the individual.

Like the statistics on mobility themselves, these results differ by education. As shown in Model 1 of Table 2.8, college graduates' log wages are .12 lower for the group in their home MSA, but high school graduates' are essentially unchanged. While this is only a starting point, it suggests that wage effect of a national labor market may differ for college graduates, and in fact high school graduates may not suffer a wage penalty from staying near parents.

2.3.5 Continuous Occupation Measure

As a continuous alternative to one-digit occupation, I use Yamaguchi's continuous measure of occupation. This is an index between 0 and 1 built from skill sets required by three-digit occupation as recorded in the Dictionary of Occupational Titles. One

key benefit to using a continuous measure is that it allows for measuring correlations and similarities in occupations across generations, but to begin with I will replace the occupation dummies with cognitive and motor task intensities in the base wage equation:

$$\begin{aligned} \ln w_{ilt} = & \beta_{0l} + \beta_{0t} + \beta_1 X_{it} + \beta_2 X_{it}^2 + \beta_3 I_t[L_{it}^f = \ell] \\ & + \beta_4 cog(j_{it}) + \beta_5 mot(j_{it}) + \nu_{ijt} \end{aligned} \quad (2.3)$$

Here, I define $cog(j_{it})$ and $mot(j_{it})$ as the individual's occupation task intensities, using these as covariates in place of W_j . These results, as shown in Model 2 of Table 2.8, have very similar point estimates for father's location as Model 1, with a slightly larger negative effect for college graduates. The cognitive skill intensity itself has positive effects on wages for both high school and college graduates.

2.3.6 *Father's Occupation and Wages*

The next step I take is to include father's occupation in the wage equation. There are at least two simple explanations for why fathers in occupations with higher cognitive intensities might correlate to sons with higher wages in these regressions, even after accounting for sons' own occupations. The first is that including father's occupation may provide an additional signal of the son's unobserved qualities. A second explanation is that the father may want to help the son in the labor market directly, and fathers in certain occupations are in a better position to do so. If this results in more good job matches or favorable treatment, then sons's wages may be sensitive to father's occupation.

While I emphasize that the regressions in this stage of the paper are descriptive, they can show whether father's occupation has any explanatory power at all on the son's wages. If not, than neither of the above stories are likely to explain wages. With

this in mind, I run a regression that includes father's occupation's task intensities, which I denote using f superscripts.

$$\begin{aligned} \ln w_{ilt} = & \beta_{0l} + \beta_{0t} + \beta_1 X_{it} + \beta_2 X_{it}^2 + \beta_3 I_t[L_{it}^f = \ell] + \beta_4 cog(j_{it}) + \beta_5 mot(j_{it}) \\ & + \beta_6 cog(j_{it}^f) + \beta_7 mot(j_{it}^f) + \nu_{ijlt} \end{aligned} \quad (2.4)$$

Under this formulation, Model 3 in Table 2.8, I find that the cognitive intensity of father's occupation has a positive correlation with wages for both high school and college graduates. The son's own cognitive intensity continues to be associated with higher wages and being in the father's location continues to have a negative correlation with college graduates' wages, both effects that were seen in the previous specifications.

Next, I take one other step and look at family proximity. The father may have more influence in his own labor market than he will if his son lives far away, but any completed transmission of human capital through investment or unobserved ability should benefit the son in any market. This is a way that may help distinguish the two theories above. Continuing to define father's location as L_{it}^f , I run the equation with the following interaction terms:

$$\begin{aligned} \ln w_{ilt} = & \beta_{0l} + \beta_{0t} + \beta_1 X_{it} + \beta_2 X_{it}^2 + \beta_3 I_t[L_{it}^f = \ell] + \beta_4 cog(j_{it}) + \beta_5 mot(j_{it}) \\ & + I_t[L_{it}^f \neq \ell] * (\beta_6 cog(j_{it}^f) + \beta_7 mot(j_{it}^f)) \\ & + I_t[L_{it}^f = \ell] * (\beta_8 cog(j_{it}^f) + \beta_9 mot(j_{it}^f)) + \nu_{ijlt} \end{aligned} \quad (2.5)$$

Across education groups, the pattern on point estimates is that the father's occupation's cognitive intensity was relatively more strongly associated with son's wages when father and son lived in the same location, and father's occupation's motor intensity was more strongly associated with higher son's wages when they did not live

in the same location. This is seen in Model 4 of Table 2.8. Father’s occupation’s cognitive intensity was positive and significant when in the same location for high school graduates and college graduates.

The final specification I will consider (Model 5 of Table 2.8) is to test whether occupational similarity between fathers and sons affect wages. The previous regression includes father’s characteristics, but it presumes that there is an absolute advantage or disadvantage associated with a father’s occupation. Here, I will add a measure of occupational distance to the specification, where distance is measured $occdist(j_{it}, j_{it}^f) = \sqrt{(cog(j_{it}) - cog(j_{it}^f))^2 + (mot(j_{it}) - mot(j_{it}^f))^2}$. The full specification is:

$$\begin{aligned} \ln w_{it} = & \beta_{0t} + \beta_{0t} + \beta_1 X_{it} + \beta_2 X_{it}^2 + \beta_3 I_t[L_{it}^f = \ell] + \beta_4 cog(j_{it}) + \beta_5 mot(j_{it}) \\ & + I_t[L_{it}^f \neq \ell] * (\beta_6 cog(j_{it}^f) + \beta_7 mot(j_{it}^f) + \beta_{10} occdist(j_{it}, j_{it}^f)) \\ & + I_t[L_{it}^f = \ell] * (\beta_8 cog(j_{it}^f) + \beta_9 mot(j_{it}^f) + \beta_{11} occdist(j_{it}, j_{it}^f)) + \nu_{ijk} \end{aligned} \quad (2.6)$$

In this formulation, the effects for high school and college graduates of occupational task intensity, both of the son and father, are similar to the results from Model 4. College graduates in the same location as fathers tended to have higher wages when occupational distance was high, meaning the occupations were dissimilar in cognitive/motor space, and high school graduates had higher wages when occupational distance was high and they were in different locations from their fathers.

In this section of the paper, I have done three things. First, I have established the PSID subsample I will use empirically and provided summaries of young adults’ geographic mobility and intergenerational correlations with their parents, finding similar levels of mobility and correlation in the PSID to what others have found using other data. In establishing intergenerational correlation of occupation, I have also introduced Yamaguchi’s continuous measure of two-dimensional occupation task in-

tensity, which I will continue to use in the structural model as my primary method of characterizing occupations. Finally, I have shown descriptive evidence that parents' characteristics and location correlate with son's wages. In particular, the regressions establish two major patterns. College graduates tend to have lower wages when in the same MSA as their fathers, but this is not true for high school graduates. Also, for both high school and college graduates, an individual's wages tend to be higher when his father is both in an occupation with a high cognitive task intensity and is in the same MSA as he is.

Since these regressions do not have any way of distinguishing between possible reasons for these patterns, my preferred interpretations of these correlations is not as strong evidence per se for the impact of fathers on son's wages, but as evidence that the question is worthy of further exploration. The goal of the next section of the paper will be to build a model under whose assumptions the effects of preferences for family, unobserved similarities between fathers and sons, and direct labor market effects fathers can have on sons are distinguished.

2.4 Model

While informative about the correlations in the data, the descriptive regressions are not able to value wage outcomes against non-monetary preferences or distinguish between channels of parental influence. The results in the previous section may represent the combination of a number of ways fathers' attributes correlate with sons' accepted wages. First, information about the task intensities of the father's occupation may be a signal of the son's ability that would otherwise be uncontrolled for. Second, fathers in certain types of occupations may have the local influence to intercede for their sons in the labor market, and those sons gain higher wages either through nepotism or because they are better matched to occupations where they can be most productive. Third, sons may consider proximity to parents to be

an amenity of their parents' location and therefore be willing to accept lower wages in their father's location than they would be willing to take elsewhere. All of these factors may be acting on son's wages, and the descriptive regressions will not be able to determine anything beyond the sum of these effects.

In order to address these issues, I set forth a model of location choice, parental co-residence and occupation switching decisions of young adults. Agents choose where to reside, whether to seek a new occupation and whether to enter the labor market at all in each period. At the beginning of every period, an agent may either be employed or not and may be living in a parent-headed household or a self-headed household.¹¹

The model is designed to incorporate choices that cannot be fully accounted for in the wage regressions of the previous section. The choice model allows for preferences, human capital transmission, and networking effects of parents to be distinguished from separate sources of variation in the data. I can also build in partially unobserved ability and job match measures and allow agents to be forward-looking. The total effect of building in these model features is to allow me to say, under the assumptions of the model, what causes the patterns of correlation between parents' attributes and sons' wages that are shown in the previous section. In the subsections below, I will discuss what elements of the model are designed to account for each of the channels by which parents affect sons' decisions and wages. The model serves two major purposes. First, by embedding the wage equation into a fuller choice model, I can account for the selectivity of movers, across both locations and occupations. Secondly, I am also interested in the preference values themselves and how they affect propensity to migrate across locations and switch occupations.

¹¹ I abstract from other living situations (with grandparents or other friends or relatives) since these are rare cases. For the exposition of the model, I will also discuss moving out of the parents' household as a one-way decision, although in reality there are a small but non-trivial number of young adults that move out and later move back. With additional parameters or assumptions, the model can be extended to this case.

The choice model provides three main channels for parents to affect adult children’s wages. The first channel is through preferences, in which children like to live near their parents and may stay nearby rather than seek out labor markets with higher wages. This is analogous to the “tied stayer” incentive that is the focus of most of the intra-household family migration literature originating from Mincer. The second channel is through human capital. Agents will enter the labor market with fixed cognitive and motor abilities which represents all inputs in childhood, whether by genetics, parental investment, primary school education or other reasons. I will make no effort to distinguish the impact of these childhood inputs relative to each other, but rather am only interested in accounting for their total effect on labor market outcomes. These abilities are intrinsic to an individual and do not change over time, unlike the occupational task intensities that I have discussed in the previous section and will use again in the model. The returns to these abilities in the labor market, as I will show when forming the wage equation, will depend on interactions with the task intensities of the current occupation. Parents’ education and average occupation and employment information enter into the child’s ability measures, and the manner in which they enter is not dependent on where the parents live (or whether they are still living). The third channel is through labor market intervention. I allow father’s occupation and the occupational distance¹² between father and son’s current occupations in cognitive-motor space to enter directly into the son’s wage equation *only if* they are in the same location. I attribute any effect of this, remaining after adjusting for the son’s preferences and abilities, to the father’s ability

¹² I consider only father’s characteristics for this direct effect for two reasons. First, the literature supports the notion that transmission of occupation from father to son is much stronger than mother to son. Second, in descriptive regressions in which I used both mother and father’s occupation measures, the effect of mother’s characteristics on sons’ wages and occupation were weaker than the effect of father’s characteristics overall and also showed less sensitivity to interactions with whether parent and son lived in the same location. Thus, I exclude mother’s characteristics from the direct wage and occupation transition effects, while leaving them in the ability measures.

to directly improve his son’s labor market outcomes ¹³

2.4.1 Model Timing

In this section, I discuss timing of the agent’s decisions and realizations. Before completing his education, the agent has not made any relevant decisions to the model. I assume he is living in his parents’ household and has no work experience or occupation. In the first period of adulthood, I assume that the agent enters the labor market for the first time, by a process I do not model explicitly as I will for future periods. At the end of this initial period, I assume that he observes not only his wage $\ln w$, but he also has an accounting to determine what is attributable in his realized wages to his forecast errors, which are defined in the wage subsection below as $\zeta_{i,cog}$ and $\zeta_{i,mot}$, his match quality, θ_{ij} , and his transient error, ν_{it} . Therefore, after this first period agents know the true values of their abilities, although the econometrician does not observe the error decomposition must still determine probabilities the agent is in given types of ζ s and θ . This means that from the agent’s perspective, there is no learning in the model after period one. All periods after the first will be the same, with the only information updating being new realizations of any time-varying state variables.

Following the first period, I assume the model timing is as follows. At the beginning of the period, the agent knows his parents’ location, father’s occupation, and current marital and fertility status. He receives preference shocks and observes his utility in various choices up to his expected counterfactual wages. I also assume that if he gets married or has his first child, these happen at the end of the period so

¹³ This relies on the identifying assumption that any intervention of the father’s through better information or networking or any other cause can only be done when father and son are in the same labor market. This seems a good first step, especially for scenarios as in the literature where the father may help the son find a job at his own plant or with his own employer. The current model will not account for the possibility that some fathers may have connections in other labor markets and could therefore help their sons at a distance, except to the extent this could be considered to be part of the son’s “permanent ability” measure.

he will go into the next period with an updated family status. Furthermore, any parent mortality is assumed to occur at the end of the period and that living parents announce their any changes in location, occupations and employment status in between periods, so that the agent can account for these when making next period choices.

2.4.2 Choice Set

In each period after the first, agents make a choice about their location and occupation. The size of the choice set depends on the conditions from the previous period. While the location and occupation decisions are actually modeled as one joint choice, I will first lay out the possibilities in each dimension separately to explain the intuition.

The first period of adulthood is either age 18, for those who do not have any post-secondary education, or else the first year after full-time education is completed for those who attended college, and this is the period in which agents learn their abilities. The education decision itself is taken as given. In the final period before the agent enters adulthood (time zero), he is assumed to live in his parents' household, which itself is located in a US state or MSA, depending on the unit used. This is called the agent's "home location," which will never change regardless of own or parents' moves later.

In every period after the first, the agent chooses to live in one of five locations. First, he can always choose to remain in his current location, which I call the "stay option. Second, he can always move to his home location. Third and fourth, he can always choose to move to his father's or mother's current location. Finally, he can make what I will refer to as a "national move," which covers all other locations in the US. In this case, the agent does not choose between locations, but rather chooses to move and is randomly assigned to another location according to a transition process.

This can be thought of as an abstraction of making a national labor market search and taking the best option among those. Since some of these definitions will overlap in practice, agents have somewhere between two and five location choices depending on their current living situation. The Stay and National choices are always available. The Home, Mother and Father options will be distinct from these two and from each other only if the agent or parent has moved in previous periods. Thus, all five options will be present only in the unusual case in which parents are separated and the agent and both parents all live in different locations from one another and the original home.

A special case occurs for agents who begin a period not only in their parents' location, but still in their parents' household. In this case, an agent's Stay choice is to remain in the parent's household, and the parent choice is to establish their own household in that location. I view moving out as a one way choice; in the model, agents who have established their own households may never move back in with their parents.¹⁴

Occupation decisions work in a roughly analogous manner to location. In the model, an agent never chooses an occupation per se. Rather, they have an option to seek a new occupation, matching with an occupation according to some transition probability that is a function of their observed and unobserved individual characteristics. Conceptually, they may choose to enter an "occupation lottery" for a new occupation draw, but with their draw weighted by abilities and current occupation. Similarly to the National location move, this is an abstraction of a process in which the agent finds a new best available occupation.

Employed agents have three choices. They may stay in their current occupation,

¹⁴ This assumption is for simplicity and to separate those who never move out (and never become PSID heads of household) from those who move back after having lived independently. My framework could be written to allow individuals to return to parents' households, and this is a question I plan to revisit in the future.

choose to not work, or choose to change occupations but remain in the labor market. In the latter case, they will enter a new occupation with certainty; in terms of the model, this means that those who pay the occupation switching cost will in fact switch occupations rather than test the market and return to their current occupation. This is the only way to change occupations. In the model, there is no exogenous job destruction and anyone who wishes to work will become employed. Since I model location and occupation decisions jointly, I consider a staying decision to be remaining in the same location and occupation. An occupation spell, in this context, is a location-occupation pair. If an agent makes a geographic move, they will automatically have to reset their occupation tenure and pay the occupation switching cost, no matter what occupation they enter into in the new location.

My occupation switching process differs in a few ways from a standard job search model. For one, I am interested in occupations, not jobs, meaning that I am not working with firm-specific matches or firm-specific human capital. Second, there is no learning for the agent about his own abilities or matches after the first period. He observes his own ability at the end of his first period of adulthood, and if he chooses an occupation switch in future periods he will immediately enter a new occupation and observes his location-occupation match quality at the end of that period. However, while he knows the distributions he will draw from, he is not permitted to observe these realizations before making the decision to switch. This model also means that my occupation switching cost may have a somewhat different interpretation from a standard job search cost. Since my occupation switching is undirected, there may be a cost associated with the reality of higher skill occupations being less substitutable for one another. If this depresses the number of high-skill occupation changes, this may be partially attributed to switching cost.

Therefore, household heads have three labor market choices in their current location (keep their current occupation, switch occupations, and not work) plus two

choices times the number of possible moves (work and not work for each location choice), for somewhere between five and eleven choices. Agents in parent-headed households face a similar choice set, but we do not observe occupation for non-heads. Therefore, the Stay option for non-heads is only crossed with the decision of whether or not to work. They also may always choose to establish their own household in the current location, and by definition begin the period in the same location as at least one parent. This results in six to ten choices. In all cases, the agent takes parents' location and occupations as given at the point of decision-making.

The agent is motivated by utility derived from wages, preferences for home and parents as well as preferences for employment and household headship, location and occupation switching costs, and random preference shocks. Preferences and moving costs may change based on whether the agent is married or has children. Wages are partially dependent on occupation task intensity, experience, occupation tenure, parents' proximity and characteristics, own ability, location-occupation match quality. In the following sections, I will describe in detail how the agent values each of the above factors.

2.4.3 Utility

In each period, the utility takes the form:

$$\begin{aligned}
u_{ijlt} + \varepsilon_{ijlt} = & \alpha_1 * \ln Wage_{ijlt} \\
& - (\alpha_2 + \alpha_3 mar_{t-1} + \alpha_4 child_{t-1}) I_t[l \neq l'] \\
& - \alpha_5 (I_t[j \neq j'] | I_t[l \neq l']) \\
& + (\alpha_6 + \alpha_7 mar_{t-1} + \alpha_8 child_{t-1}) I_t[L^p = \ell] \\
& + \alpha_9 I_t[H^p = 1] \\
& + (\alpha_{10} + \alpha_{11} mar_{t-1} + \alpha_{12} child_{t-1}) I_t[home = \ell] \\
& + \alpha_{13} I_t[emp_{it} = 0] + \alpha_{14} I_t[H^p = 1] I_t[emp_{it} = 0] + \varepsilon_{ijlt} \quad (2.7)
\end{aligned}$$

where i indexes individual, j occupation, l location, t time, p parent, and j' and l' previous occupation and location. I use emp_{it} indicate whether i was employed in period t , a value of zero indicating non-employment, and mar_{it} and $child_{it}$ to indicate whether the agent is married or has children, respectively, at time t , with mar_{it} taking a value of 1 for married individuals and $child_{it}$ 1 for individuals with at least one child. L^p indicators are 1 if at least one parent lives in the same location ℓ as the individual, but is not co-resident, and H^p indicators are 1 when the agent is in the same household as at least one parent.¹⁵

Wages are a key component of utility I will discuss in the next section, and there are a number of other factors that affect utility as well. I include moving costs, occupation switching costs, preferences for living in the fixed home location or near parents, and a utility from not working in the labor market in the model.

Any time the agent changes locations, a moving cost is paid. The moving cost, represented by α_2 , α_3 and α_4 , is a function of marital and fertility status, as well as a baseline cost for any move. This cost is for moves is across geographic locations

¹⁵ I considered alternative specifications in which preferences were allowed to vary by mother and father's location separately, but these did not result in substantially different parameter estimates so I present the simpler form here and in the empirical results.

only; the cost to establish one's own household from the parent's household without leaving the parents' location is not identified separately from the utility value of remaining in the parents' household.

Similarly, agents must pay a constant switching cost α_5 to switch occupations within a location or to search for an occupation after making a geographic move.

Agents receive utility from residing in the same location¹⁶ or household as parents and in the fixed home location, which can be modified based on marriage and fertility status. Non-employed agents also receive a utility benefit, interpretable as leisure, home production or a combination thereof, which is further interacted with living in a parent's household. In the model, preferences for parents' location are represented by α_6 , α_7 and α_8 , parents' household by α_9 , home location by α_{10} , α_{11} and α_{12} , and non-employment by α_{13} and additionally α_{14} when in parents' household.

In the static model, agents choose the option that gives the most flow utility. In the dynamic case, they maximize discounted utility over time.

2.4.4 Wages

The wage equation is as follows. Before accounting for parental characteristics, the wage equation takes the form specified by 2.8.

¹⁶ In the empirical specification, MSA

$$\begin{aligned}
\ln w_{ijt} = & \beta_t \beta_{0t} + \beta_l \beta_{0l} \\
& + \beta_1 X_{it} + \beta_2 X_{it}^2 + \beta_3 X_{it} * \text{cog}(j_{it}) + \beta_4 X_{it}^2 \text{cog}(j_{it}) \\
& + \beta_5 X_{it} * \text{mot}(j_{it}) + \beta_6 X_{it}^2 \text{mot}(j_{it}) \\
& + \beta_7 T_{it} + \beta_8 T_{it}^2 + \beta_9 T_{it} * \text{cog}(j_{it}) + \beta_{10} T_{it}^2 \text{cog}(j_{it}) \\
& + \beta_{11} T_{it} * \text{mot}(j_{it}) + \beta_{12} T_{it}^2 \text{mot}(j_{it}) \\
& + \beta_{13} \text{cog}(j_{it}) + \beta_{14} \text{mot}(j_{it}) + \beta_{15} \text{cog}(j_{it}) * \eta_{i,\text{cog}} + \beta_{16} \text{mot}(j_{it}) * \eta_{i,\text{mot}} \\
& + \beta_{17} X_{it} * I_t[H^p = 1] + \beta_{18} X_{it}^2 * I_t[H^p = 1] \\
& + \beta_{19} I_t[H^p = 1] * \eta_{i,\text{cog}} + \beta_{20} I_t[H^p = 1] * \eta_{i,\text{mot}} + \theta_{ij} + \nu_{it} \tag{2.8}
\end{aligned}$$

Log wages are a function of the vector of location dummies β_{0l} and year dummies β_{0t} , general experience X , job tenure T , occupational task intensities $\text{cog}(j_{it})$ and $\text{mot}(j_{it})$, permanent cognitive and motor skill $\eta_{i,\text{cog}}$ and $\eta_{i,\text{mot}}$, which will be described more fully in the discussion and formulation of Equations 2.9 and 2.10 below, job match quality θ_{ij} , whether the individual is the head of household, and interactions of experience, tenure, location, and skill with the task intensities of the occupation. This setup is a modification of standard wage equations in the literature to the two-dimensional framework of occupation I am using in my model. Ideally, I would have the same information on everyone, but for non-heads, occupation is not observed. In those cases I set task intensities and occupation tenure to zero, treating non-headship as if it were another occupation with its own return to experience as well as cognitive and motor ability. In the timing of the model, the agent will learn his θ_{ij} at the end of the period if he is in a new location-occupation pair, or he keeps his θ draw if he is in the same pair as the last period. When he is deciding whether to switch occupations, he will not know what draw of θ_{ij} he will receive in his new occupation until after he decides to work there.

This specification in 2.8 differs in several key ways from the descriptive regressions from the previous section. While I reuse β notation, these are different from the previous coefficients. The introduction of the η abilities allows me to treat occupation task intensities differently. In this equation, what is related to higher returns is not the task intensities themselves, as in the descriptive regressions, but the match of an occupation's tasks to human capital of the individual. An individual in an occupation with high cognitive task intensity may see little return if his ability $\eta_{i,cog}$, experience and occupation tenure are low. Correspondingly, returns to high values of η s, experience or tenure will be muted in occupations whose task intensities are low. The match quality θ_{ij} will also play a role.

Next, I form the forecasting equations for the cognitive and motor abilities $\eta_{i,cog}$ and $\eta_{i,mot}$. Upon entering adulthood, he does not know them with certainty. He instead forecasts his ability $\eta_{i,cog}$ and $\eta_{i,mot}$ using both parents' education and occupation history as signals for his own cognitive and motor ability. In Equations 2.9 and 2.10 below, parents' characteristics \overline{cog} , \overline{mot} , and \overline{NW} denote the average task intensities and labor force attachment of the parent over all waves they appear in the analysis sample.¹⁷ *Educ* variables, superscripted by parent, indicate dummies for the four levels of education defined in the earlier sections of the paper. The errors in the son's time-zero forecast are $\zeta_{i,cog}$ and $\zeta_{i,mot}$, which he will discover at the end of the first period upon entering the labor market but will always be unobserved from the perspective of the econometrician.

$$\begin{aligned} \eta_{i,cog} = & \phi_{1,cog}Educ^f + \phi_{2,cog}Educ^m + \phi_{3,cog}\overline{cog}^f + \phi_{4,cog}\overline{mot}^f + \phi_{5,cog}\overline{NW}^f \\ & + \phi_{6,cog}\overline{cog}^m + \phi_{7,cog}\overline{mot}^m + \phi_{8,cog}\overline{NW}^m + \zeta_{i,cog} \end{aligned} \quad (2.9)$$

¹⁷ Years not in the labor force are ignored when determining parents' mean task intensities.

$$\begin{aligned}
\eta_{i,mot} = & \phi_{1,mot}Educ_f + \phi_{2,mot}Educ_m + \phi_{3,mot}\overline{cog}^f + \phi_{4,mot}\overline{mot}^f + \phi_{5,mot}\overline{NW}^f \\
& + \phi_{6,mot}\overline{cog}^m + \phi_{7,mot}\overline{mot}^m + \phi_{8,mot}\overline{NW}^m + \zeta_{i,mot}
\end{aligned} \tag{2.10}$$

One important feature of the forecast equations is that they are based entirely on variables that will not change with time. Parents' education and average occupation task intensities are meant to be signals of parental ability and suitability for occupations that they pass along to their children. Average occupation intensity is an imperfect measure because it relies on what the parents do (in terms of occupation history) as a signal for the son's ability, but since parents' history is necessarily truncated at the beginning of the panel and their own parents' information will not be available, occupation is still useful information to form the signal.¹⁸ Crucially, though, nothing in the η equations is dependent on where parents are in relation to the son, or even whether they are still living. It is therefore not meant to include any networking effect fathers may have on son's occupation or wages, which I will add into the wage equation separately.

A key element of η is the forecast error ζ . This ζ is the difference between true ability η and forecasted ability $\hat{\eta}$. The agent will rapidly learn his realization of $\zeta_{i,cog}$ and $\zeta_{i,mot}$, as detailed in Section 2.4.1, but from the perspective of the econometrician this will always be unobserved and it must be inferred from the son's outcomes and decisions how likely he is to have a good draw of the ζ components of ability. It is also worth noting that while I interpret ζ s to be forecast errors on individual ability that are important to account for in my analysis, it is not a point of emphasis

¹⁸ Because parents are older and more established, they are less likely to be observed switching occupations and may therefore be in better matches than their children, and their occupational task intensity may be a good signal for their own ability. However, it is true that task intensity is a characteristic of the parents' occupation and not of the parents themselves (as education is), and in future work I would like to test the robustness of the model to alternative measures of parental ability in the signaling equations.

how to interpret the ϕ coefficients. In studying parents' effects, I am interested in separating any network effects of wages from other explanations such as non-wage utility from parents, which is included in Equation 2.7, and parental influence on the son's ability, but I am not trying to decompose the process by which parents may transmit that ability. Therefore, I want to isolate the ζ terms because I assume they are a point of difference between the agent and econometrician's information set, but I do not attempt to provide insight on any mechanisms by which parents may, in fact, contribute to the production of their son's ability¹⁹.

To account for contemporaneous effects fathers may have in helping their sons find better wages, I add father's occupation characteristics directly to the wage equation in 2.8 to form Equation 2.11.

$$\begin{aligned}
\ln w_{ijt} = & \beta_t \beta_{0t} + \beta_l \beta_{0l} \\
& + \beta_1 X_{it} + \beta_2 X_{it}^2 + \beta_3 X_{it} * cog(j_{it}) + \beta_4 X_{it}^2 cog(j_{it}) \\
& + \beta_5 X_{it} * mot(j_{it}) + \beta_6 X_{it}^2 mot(j_{it}) \\
& + \beta_7 T_{it} + \beta_8 T_{it}^2 + \beta_9 T_{it} * cog(j_{it}) + \beta_{10} T_{it}^2 cog(j_{it}) \\
& + \beta_{11} T_{it} * mot(j_{it}) + \beta_{12} T_{it}^2 mot(j_{it}) \\
& + \beta_{13} cog(j_{it}) + \beta_{14} mot(j_{it}) + \beta_{15} cog(j_{it}) * \eta_{i,cog} + \beta_{16} mot(j_{it}) * \eta_{i,mot} \\
& + \beta_{17} X_{it} * I_t[H^p = 1] + \beta_{18} X_{it}^2 * I_t[H^p = 1] \\
& + \beta_{19} I_t[H^p = 1] * \eta_{i,cog} + \beta_{20} I_t[H^p = 1] * \eta_{i,mot} + \theta_{ij} \\
& + \left(\beta_{1f} cog(j_{it}^f)^f + \beta_{2f} mot(j_{it}^f)^f + \beta_{3f} occdist(j_{it}, j_{it}^f) \right) I_t[L_{it}^f = \ell] + (2.11)
\end{aligned}$$

¹⁹ This is in contrast to a long literature interested in how genetics, environment and schooling combine to form childhood production functions; see Todd and Wolpin (2003) for an overview. An interesting point, but well beyond the scope of this paper would be to study young adults who had reached the same η s through different combinations of production inputs would have different location decisions and contemporaneous effects of parents. By using a non-structural signaling equation for η s, I am assuming this is not the case.

Here, I use occupation characteristics crossed with location for the same reasons as in the descriptive regressions, to measure the possibility that fathers impact sons' wages in a given occupation and that this may depend on the father's occupation and how similar sons' and fathers' occupations are. Because equation 2.11 includes father's present-day occupation characteristics and location, I interpret any effect of β_{1f} , β_{2f} and β_{3f} as due to networking, whereas significant coefficients of parents in signaling equations 2.9 or 2.10 above are permanent and are assumed to reflect transmission of ability through any process that acts before adulthood. Note that this equation relies on father's contemporaneous occupation and that fathers and sons are in the same location ℓ . This will not capture networking effects that may happen at a distance²⁰, but using variation in relative location and occupation between fathers and sons builds from the literature in which fathers help sons find work through local connections and provides scope for separating network effects from transmission of ability or signaling.

2.4.5 Occupation Switching

In determining counterfactual wages, it is important to know not only what wages agents expect to earn given an occupation, but what type of occupation an agent would expect to get if he chose to leave his current occupation (or enter the labor market, if not currently employed). To this end, I write transition equations for the next period cognitive and motor task intensities:

$$\begin{aligned}
cog(j_{i,t+1}) &= \gamma_{0,cog} + \gamma_{1,cog}cog(j_{it}) + \gamma_{2,cog}mot(j_{it}) + \gamma_{3,cog}I_t[emp_{it} = 1] \\
&\quad + \gamma_{4,cog}I_t[H^p = 1] + \gamma_{5,cog}\eta_{i,cog} + \gamma_{6,cog}\eta_{i,mot} \\
&\quad + \left(\gamma_{7,cog}cog(j_{it}^f) + \gamma_{8,cog}mot(j_{it}^f) \right) I_t[L_{it}^f = \ell] + \iota_{it,cog}
\end{aligned} \tag{2.12}$$

²⁰ For example, in national markets such as law or academia, a father's network or reputation may help the son's prospects in other cities.

$$\begin{aligned}
mot(j_{i,t+1}) = & \gamma_{0,mot} + \gamma_{1,mot}cog(j_{it}) + \gamma_{2,mot}mot(j_{it}) + \gamma_{3,mot}I_t[emp_{it} = 1] \\
& + \gamma_{4,mot}I_t[H^p = 1] + \gamma_{5,mot}\eta_{i,cog} + \gamma_{6,mot}\eta_{i,mot} \\
& + \left(\gamma_{7,mot}cog(j_{it}^f) + \gamma_{8,mot}mot(j_{it}^f) \right) I_t[L_{it}^f = \ell] + \iota_{it,mot} \quad (2.13)
\end{aligned}$$

These equations, with independent draws of $\iota_{it,cog}$ and $\iota_{it,mot}$, govern how agents are placed into a new cognitive-motor pair if they choose to separate from their current occupation, or for unemployed or non-head workers if they choose to become employed and a head of household. This transition is based only on current occupation task intensities, ability, father's current occupation task intensities and relative location, and the current employment and headship status of the agent. I include fathers' current occupation characteristics in this occupation switching transition in the same way as the wage equation, allowing for the possibility that through local network effects fathers might affect not only affect sons' wages within an occupation, but may also affect their outcome when switching occupations. In writing the problem this way, I rely on the simplifying assumptions that the occupation transition is Markovian, and that agents make the decision to change occupations before observing the characteristics of their potential new occupation. Under these model assumptions, I can build expected values for workers' task intensities conditional on making an occupation switch, which allows me to compute counterfactual expected wages for the choice to switch occupations as well as the choice to remain in the current occupation. An agent who enters the lottery will not know what his $\iota_{it,cog}$ and $\iota_{it,mot}$ will be before entry. If he does choose to switch occupations, he receives his ι draws and enters a new occupation.

2.4.6 Demographic Transitions

There are a few major dimensions in which agents in the model must form expectations in order to make decisions. The sources of utility in the model are wages, proximity to parents and fixed home locations, leisure (non-employment), and interactions of life cycle factors with parents and home location. In making occupation and employment decisions, the agent must know his wage prospects if he switches occupation or location. I use the wage and occupation transition equations described in the previous subsections to allow each agent to form expectations about wages. In making location decisions, the agent must know something about his parents' future decisions, his own likelihood to get married and have children, and how his national moves are resolved. I describe how I estimate those transitions in this section.

I will not model parents' decisions or individuals' marriage and fertility outcomes directly, but rather I assume these can be characterized by transition probabilities that can be inferred from the data. In the model, there are two main elements that make one location more favorable than another. The first is high wages, which are beneficial to all agents. The second is personal ties to the location, whether it is the home or parents' location. In the static case, I treat all these ties as fixed; an agent has one permanent home location, and parental location decisions are known to the agent at the time of his own decision-making. In the dynamic case, home is still fixed, but parents might not be. The agent must account for a possible parental transition. If locating near parents is valuable either in or out of the labor market, the value may still be offset if parental mobility is high. It may not be worth the moving cost to gain the proximity benefits today if they will move away tomorrow.

Parental moves, in the model, are governed by a transition process that I take from Census data. Since older individuals are not very mobile, there are too few parental moves in the PSID to reliably estimate parents' moves. Therefore, I will

incorporate outside data from the Census to estimate these transitions. I find the probability of moving for each age and education status using the Census and match to PSID respondents' parents age and education to estimate their probability of moving. Using the same criteria, I determine the likelihood of each destination. For individuals aged 45-65, the bulk of the parents' ages in the model, I estimate the probability of moving as a logit.

$$P(move_t^p) = f(age_t^p, HSGrad^p, Coll^p, CollGrad^p) \quad (2.14)$$

My functional form includes coefficients of age, age squared and dummies for high school graduates, some college (including two year degrees), and four year college graduates (including graduate degrees), with less than high school omitted.

For destinations, I take the same sample and place them into $M+1$ locations, using the M MSAs that have the most observations in the PSID²¹ and location zero, which incorporates all others.²² I then build an $(M + 1) \times (M + 1)$ transition matrix for movers between MSAs using the 1980 and 1990 Census questions about where individuals lived five years ago, with location five years ago on one axis and current location on the other. I use the 1980 matrix for years 1976-84 and 1990 for 1985-93. For movers, I then take the probability of the destination directly from the data, using the observed moves from the transition matrix.

I use a similar method to determine own destinations when making “national moves,” the designation I reserve for all moves that are not to home or parents' location in order to compress the choice set. In the model, an agent that makes a national move does not know where his best option is going to be, just as an agent

²¹ Empirically, I use the 20 most common MSAs in order to have sufficient density to estimate wage dummies by location from the PSID.

²² I do track where precisely individuals live in determining whether they have moved, such that a move from location zero to a “different zero” is possible, but individuals in $M \neq 0$ in consecutive periods have by definition not moved.

making an occupation switch does not know what new occupation he will enter. In order to compute counterfactual wages, I need to have a transition matrix to determine the probability, given the agent's current location and education, that a national move will result in a move to any particular location. Again, to ensure sufficient density of moves to make this transition matrix, I use the same Census data. Available Census data is not a perfect analogue to the decision-making that I model with the PSID, but it does have information on previous location and birth state. I build an $M+1$ by $M+1$ transition matrix on Census moves among 23-35²³, but I eliminate any moves in which the individual's current location is the birth state. Because I do not have birth MSA, I use this as a proxy for moves home or to parents, counting the others as national moves. I use birth state as a proxy for home location, and thus consider any move whose destination is not birth state a "national move." I then use the observed transition probabilities directly as my weighting for the destination of a national move.

Finally, I assume marriage and fertility, while obviously choices in reality, are exogenous to the model. For single men in the PSID, I assume likelihood of marriage depends on age and education, and fertility on age, education and marital status. For simplicity, I abstract from number and age of children in favor of only whether the individual has children or not, so the transition is only from childless to having children. For fertility, I add a dummy for being married.

$$P(mar_{it} = 1 | mar_{i,t-1} = 0) = g(age_{it}) \quad (2.15)$$

$$P(child_{it} = 1 | child_{i,t-1} = 0) = h(age_{it}, mar_{i,t-1}) \quad (2.16)$$

Again, I use logit specifications on quadratics of age, and in this case instead of including education as a regressor I run the model separately for high school and

²³ Because the 1980 and 1990 migration questions ask residence five years ago, I use 23 as a cutoff point so that my moves are for individuals going from 18-23 on the younger end and 30-35 on the older end.

college graduates. These are not elements of particular interest in the model but rather are included as controls that can affect the value of living near parents or home as well as the cost of moving.

2.5 Estimation

I estimate the model separately for the high school graduate and college graduate PSID samples described in the data section. My estimation strategy will need to accomplish two major things that are not accounted for in the descriptive regressions but are built theoretically into the model. First, I will need to jointly estimate wage and choice parameters, because expected wages affect choices and choices, particularly the decision whether to live near fathers, affect expected wages and occupation. Second, I will need to estimate the likelihood each individual takes on certain values of unobserved parameters ζ and θ , which affect wage and occupation switching. Before I discuss the implementation of the estimation procedure, I will discuss how each of these factors help to address selectivity problems that would otherwise be present in my analysis.

One key element is that by embedding the wage equation into a full choice model, I will be able to evaluate the wage effects from parents that remain after accounting for a non-wage preference for living near parents that can cause accepted wages to be lower in the same location as parents. Unadjusted data and descriptive regressions provide a combination of both the preference and any network or other labor market effects. Greater detail of parental wage effects are added by allowing parents' characteristics to enter separately in the forecast of abilities $\eta_{i,cog}$ and $\eta_{i,mot}$, in direct effects on the wage and occupation transition equations when proximate, and via compensating differentials through the choice utility parameters. This is one of the most important ways in which the model builds on the existing literature, as most papers are either interested in mechanisms by which family members can affect job

outcomes directly, or else are accounting for preference-based family ties as a separate reason for migration from labor market reasons. The joint estimation of wages and choices allows me to measure both.

However, the point above holds for any choice model. The next question is what do I gain by including unobserved heterogeneity parameters. The match quality θ_{ij} is important for several reasons. Individuals with better occupation matches tend to stay in their occupations longer, meaning that a match quality term is vital to getting unbiased estimates of return to tenure²⁴. In my model, the occupation switching decision is influenced by match quality and by parents. Individuals tend to switch occupations either because they expect a switch to place them in an occupation where they are better matched or because they expect a switch to place them in an occupation with better characteristics, and both of these can affect the estimation of parents' effects. When agents first enter the labor market, they may shop around occupations until they find a good match, and at the same time they are at the ages where they have the highest rates of making geographic moves. Individuals in their late twenties and early thirties are more likely than younger individuals to have relocated away from parents and also to be established in good occupation matches, which could cause biased estimates of network effect of parents as well as returns to tenure and experience if match quality is not adjusted for. In certain cases, I will also show in the results that fathers living near sons affect the occupation transition equation positively, meaning that individuals near fathers have more to gain from switching occupations and therefore their switches will be less likely to be driven by poor θ_{ij} draws. Like the age profiles, this will cause individuals near fathers to have lower average match qualities than those who are not, which would cause a model without θ parameters to underestimate fathers' effects on wages within an

²⁴ Using jobs instead of occupations, Altonji and Shakotko (1987), Topel (1991) and Altonji and Williams (2005) are three classic examples using this basic structure in the returns to seniority literature.

occupation.

It is also important to correctly account for the forecast errors $\zeta_{i,cog}$ and $\zeta_{i,mot}$. The biggest reason these are important to my parameter estimates is that the returns to individual ability can be different by proximity to parents if proximity to parents correlates with other outcomes. In my wage equation, $\eta_{i,cog}$ and $\eta_{i,mot}$, the overall measures of individual ability, are in the wage equation only interacted with occupational task intensity and household headship status. If fathers in the same location can help place sons into more task-intense occupations, then individuals with high η s will be more likely to stay near parents than those with low η s, which must be adjusted for when calculating the network effect of parents. Moreover, if fathers' ability to affect occupation varies by education, as I show evidence for in Section 2.6, then the difference in differences in wages by education and proximity to parents will be partly due to differences in geographic sorting on ability between high school and college graduates. Because I assume that ζ s are forecast errors in Equations 2.9 and 2.10, they are random factors in the model. Since they are independent of the other variables in η , the same reasons for why η s may be different by proximity to parents and by education holds for ζ . If I did not include $\zeta_{i,cog}$ and $\zeta_{i,mot}$, wage differences due to these sorting of ζ s would be incorrectly be attributed to network effects or other parameters of the model.

The implementation of the estimation procedure uses the EM algorithm as described in Arcidiacono and Miller (2011) in order to estimate all parameters including discrete unobserved heterogeneity types ζ and θ , using a conditional choice probability framework developed by Hotz and Miller (1993). The basic method of the algorithm is as follows. I begin by assuming a probability that each individual in the data has given unobserved ability inputs $\zeta_{i,cog}$ and $\zeta_{i,mot}$ and occupation match θ (each taking on one of a discrete number of values; for each individual i , these inputs are collectively denoted the unobserved type of individual i). With these

values in hand, the parameters that govern the wage, occupation transition, and choice parameters can be estimated. Then, given the estimated wage and occupation transition parameters, the conditional likelihood of individual i making each choice can be estimated if he has any given combination of values for $\zeta_{i,cog}$, $\zeta_{i,mot}$ and θ . Given the relative likelihoods and the estimated population distribution of types, every individual's probability of being each unobserved type is updated, at which point the population probabilities for each type are also updated. The model is then estimated again under the new estimated type probabilities, and the process is continued until convergence of type probabilities across consecutive maximization steps. In the identification section below, I will discuss more intuitively how this process can separately identify the model parameters.

To make location and occupation switching choices, agents must form expectations of their wages in each scenario. In the model, expected wages are built in three parts. The first part is the wage equation, which is estimated to determine any individual's wages conditional on occupation, unobserved type, father's occupation characteristics when in the same location, and control variables experience, tenure, location and calendar year. The second part is the occupation transition equation, which determines expected cognitive and motor intensity of the new occupation for location or occupation switchers. The third part is the location transition for national moves, which affects the expected location component of wages for individuals who make national moves. I take this from external data.

The wage equation is estimated by maximum likelihood. As shown in the previous section, this is necessary because of the interactions between cognitive and motor task intensity and the partially unobserved ability measure which is permanent to an individual across time and occupations. It is also notable that the form of the wage equation allows for returns to experience and tenure to vary with an occupation's skill intensity.

The occupation transition equations are estimated by OLS. An occupation is treated as a cognitive and motor skill intensity pair, and the two intensities are determined by previous occupation, permanent ability, and father's occupation when in the same location. This allows for two channels in which father's occupation can affect expected wages: he may affect his son's wages within an occupation, and he may affect the characteristics of the occupation the son expects to work in relative to what he would find in another location.

With these parameter values, the agent can predict the expected value of his wage by supplying his labor in any of the markets he can choose to move to. For national moves, the expectation is taken both over wages in each possible labor market incorporated into the national option as well as the probability of a national move resulting in the agent's move to each of the possible markets. Recall that in any option requiring a job change, the agent does not observe his permanent job match θ before making his decision, but he does know the θ associated with his current occupation. His expected wage for each choice can then be used to maximize the likelihood of the choice equation.

The choice parameters are then estimated by maximum likelihood using the estimated wages from the previous step. The other utility parameters are moving costs, job switching costs, utility from not working or not forming an independent household and the value of living in the fixed home location or parents' location. In the model, employment, household formation, occupation and location mobility are determined by choices whereas parental movement and mortality, as well as the individual's own marital and fertility status, are governed by transition processes. The model can be written using conditional choice probabilities and using finite dependence.

2.5.1 Identification

At this point, I will take a step back from the details of the estimation routine to discuss the variation in the data that allows the main model parameters to be estimated. First, I consider the wage equation. There are unobserved types entered into this equation unique to an individual (ζ) and to an occupation-location spell (θ). The panel data and mobility decisions of an individual help us attribute wage variation to these factors. An individual who changes occupations and has relatively favorable wages when in a more cognitive or motor-intense occupation is likely to have high ability in that area. Similarly, an agent whose wages are higher compared to his observed attributes after an occupation move is likely to have had a relatively unfavorable wage draw in the former occupation compared to the current occupation. When wages are similar before and after, this is more likely attributable to permanent ability. There is also information to be gained from a lack of occupational mobility. An individual who stays in one occupation for a long time probably has a favorable wage draw, especially when the job attributes are not good and there would otherwise be an apparent wage gain to switching.

Location decisions primarily identify moving costs and the value of home and parents. The majority of individuals begin in their home location, so rates of initial moves combine these effects. The value of parents can be inferred in part from the high rate of return moves, in which an individual who has left in an earlier period returns to the origin location in a later period. This behavior is hard to rationalize without a preference for home or family since an income-maximizing incentive for moving will rarely result in a market worth migrating out of in one period subsequently becoming one worth returning to in the future. The other major factor in measuring parental value is by comparing individuals by parental mortality; when parents are not present, individuals should face similar moving costs and similar non-

parental values for their home location, such as other friends and social networks, as well as familiarity with and tastes for home, but will not have the same benefits in or out of the labor market that parents provide. While mobility among older people is low, there is also some variation by parental moves to distinguish home and parents.

Occupation switching costs are identified from the rate of occupation switches and the potential wage growth from switching. In the model, there are several reasons for an occupation change to affect wages. First, occupation characteristics enter the wage equation directly. There is an intercept shifter depending on task intensity, and task intensities also affect the returns to tenure and experience. This can encourage workers to stay in high task intensity occupations and switch out of low-intensity occupations. Second, switching occupations resets occupation tenure and job spell-specific match quality θ . Tenure is likely to lead to workers remaining in their current occupations, whereas the match quality will provide staying or switching incentives based on the draw. Overall, the expected effect in the absence of any costs to occupation switching is to see rapid turnover in the first few years until an occupation with good characteristics and a good match quality is found, and then very low mobility thereafter. The switching cost is essentially a measure of how much slower that process occurs than would be seen if occupational moves were free.

2.5.2 Estimating Equation

In this section, I derive the estimating equation I will use in the maximization step. Under the assumptions of additively separable flow utility, discussed in the model section, and Markovian updating of the state variables, which comes from my first step estimation of transition probabilities, then I only need conditional independence of the state variables x and error term ε in order to write the value of

a choice l_{it} in a particular state as a Bellman equation:²⁵

$$V_t(x_{it}, \varepsilon(l_{it})) = \max[v_t(x_{it}, l_{it}) + \varepsilon(l_{it})] \quad (2.17)$$

In this equation, v_t represents the flow utility plus the discounted value of V_{t+1} (whose value is summed over state transitions and integrated over errors). I employ a common strategy and assume i.i.d Type I Extreme Value errors, along with a discount factor δ that I will set equal to .95, which produces the functional form below.

$$v_t(x_{it}, l_{it}) = u_t(x_{it}, l_{it}) + \delta \sum_{x_{i,t+1}} \ln \left[\sum_{j=1}^J \exp(v_{t+1}(x_{i,t+1}, l_{i,t+1} = j)) q(x_{i,t+1} | x_{it}, l_{it}) \right] \quad (2.18)$$

This equation can be expanded by multiplying and dividing by the value of making a particular choice of $l_{i,t+1}$, where the choice is a combination of location and occupation switching decision. The expansion can be similarly expanded based on the value of a choice of $l_{i,t+2}$. This can be done any finite number of times until the current choice l_{it} makes no difference to the last value term. At that point, the future value is independent of the current choice. Then the expanded values of any two contemporaneous choices can be differenced, and by making a normalization I can write a utility function that is dependent only on utility parameters, transition probabilities, choice probabilities, and the discount rate.

Consider an agent making choice k . The value term can be expanded as follows:

²⁵ This section closely follows Bishop's (2008) application of the Hotz and Miller conditional choice probability estimation method to a similar location choice problem to this paper's.

$$\begin{aligned}
v_t(x_{it}, l_{it} = k) = & \\
& u_t(x_{it}, l_{it} = k) \\
& + \delta \sum_{x_{i,t+1}} \ln \left[\sum_{j=1}^J \exp(v_{t+1}(x_{i,t+1}, l_{i,t+1} = j) - \exp(v_{t+1}(x_{i,t+1}, l_{i,t+1} = h)) \right] \\
& q(x_{i,t+1} | x_{it}, l_{it} = k) \\
& + \delta \sum_{x_{i,t+1}} [u_{t+1}(x_{i,t+1}, l_{i,t+1} = h)] q(x_{i,t+1} | x_{it}, l_{it} = k) \\
& + \delta^2 \sum_{x_{i,t+1}} \sum_{x_{i,t+2}} \ln \left[\sum_{j=1}^J \exp(v_{t+2}(x_{i,t+2}, l_{i,t+2} = j) - \exp(v_{t+2}(x_{i,t+2}, l_{i,t+2} = g)) \right] \\
& q(x_{i,t+2} | x_{i,t+1}, l_{i,t+1} = h) q(x_{i,t+1} | x_{it}, l_{it} = k) \\
& + \delta^2 \sum_{x_{i,t+1}} \sum_{x_{i,t+2}} [v_{t+2}(x_{i,t+2}, l_{i,t+2} = g)] \\
& q(x_{i,t+2} | x_{i,t+1}, l_{i,t+1} = h) q(x_{i,t+1} | x_{it}, l_{it} = k) \tag{2.19}
\end{aligned}$$

The $\sum_{x_{i,t+1}} \ln \left[\sum_{j=1}^J \exp(v_{t+1}(x_{i,t+1}, l_{i,t+1} = j) - \exp(v_{t+1}(x_{i,t+1}, l_{i,t+1} = h)) \right]$ term is the inverse of the choice probability of choosing (h) conditional on $x_{i,t+1}$. To get the normalized value, the same equation shown for choosing (k) can be written for an alternate choice (a) . Since there is no memory of match qualities in the model, the value of choosing g in period $t + 2$ will not depend on the initial choice. Therefore, subtracting the equations and substituting in the choice probability yields:

$$\begin{aligned}
& v_t(x_{it}, l_{it} = k) - v_t(x_{it}, l_{it} = a) = \\
& u_t(x_{it}, l_{it} = k) - u_t(x_{it}, l_{it} = a) \\
& + \delta \sum_{x_{i,t+1}} \ln[P(l_{i,t+1} = h|x_{i,t+1})^{-1}]q(x_{i,t+1}|x_{it}, l_{it} = k) \\
& - \delta \sum_{x_{i,t+1}} \ln[P(l_{i,t+1} = h|x_{i,t+1})^{-1}]q(x_{i,t+1}|x_{it}, l_{it} = a) \\
& + \delta \sum_{x_{i,t+1}} [u_{t+1}(x_{i,t+1}, l_{i,t+1} = h)]q(x_{i,t+1}|x_{it}, l_{it} = k) \\
& - \delta \sum_{x_{i,t+1}} [u_{t+1}(x_{i,t+1}, l_{i,t+1} = h)]q(x_{i,t+1}|x_{it}, l_{it} = a) \tag{2.20}
\end{aligned}$$

This equation only includes utilities, choice probabilities and transition probabilities. Since the latter two are estimated in a first stage, I can find the structural parameters in the utility equation that maximize the likelihood of the observed choices in the PSID. In particular, I use agents choosing to make a national move and make the opposite employment choice in period $t + 1$ as period t (choice h) and then make a move home and choose to be not employed in period $t + 2$ (choice g). This will result in the period $t + 3$ choice to be dependent only on attributes of the home location and individual ability, as is necessary for finite dependence.

2.6 Results

2.6.1 Wages

The wage results, summarized in Table 2.9, show that fathers in the same location can have an impact on high school graduates. There is a significant positive effect of the father's cognitive task intensity and son's wage when the two are in the same location, but there is no significant effect for college graduates. There is also a smaller negative effect for father's motor intensity which is significant for both high school

and college graduates.

This is in contrast to the descriptive results, in which father's cognitive task intensity in the same location had a strong positive correlation with both high school and college graduates' wages, with the point estimate being significantly higher for college graduates. It appears from the final wage results that for college graduates, the correlation found in the descriptive regressions was due not to direct effects of fathers, but for high school graduates, direct effects were a significant reason for the correlation.

Interestingly, the patterns for returns to experience and occupation tenure differ by education group. For high school graduates, there is a high return to tenure in cognitive-intense occupations, but for the college group cognitive-intense occupations offer a very high return to general experience. This is noteworthy because college graduates may therefore have more incentive to change occupations during their career where high school graduates in a good occupation may want to hold their job and reap the benefits of their tenure-specific gain.

2.6.2 Occupations

The occupation transition results, seen in Table 2.10, also vary with education. Once again, fathers with high cognitive intensity may be able help their high school graduate sons. In this case, sons in the same location as fathers tend to obtain better (more cognitive-intense) jobs when fathers have high cognitive task intensity. There appears to be no effect in motor intensity of any father's occupation characteristics, and if anything the effect is slightly negative for college graduate sons. In all cases, previous occupation's task intensity has a significant effect, but the relationship is stronger for college graduates.

The combined effect of father's cognitive intensity on occupation and within-occupation wages of high school graduates is economically as well as statistically

significant. A one standard deviation raise in father's cognitive task intensity is associated with a 0.061 increase in the log of son's wages when in the same location. At average wages, this is a raise of \$1721 a year.

2.6.3 Choices

The choice parameters can be described in several ways. One simple way is to use the relative coefficients on wage and other utility parameters to calculate the implied dollar value of various amenities in the model, which I do in Table 2.11. Evaluated at the mean of wages, the implied moving costs for single high school and college graduates are each around \$5000 to \$7000. Agents with families face moving costs that are roughly twice as high. Parents have a very high utility value as well, equivalent to \$16,000 annually for single college graduates and \$18,000 for high school graduates. This value declines by 30-40% for married individuals without children, but then rises again once children are born. There is a lesser, but still very significant, utility value for living in the fixed home MSA. This value increases somewhat with marriage and children.

Before using the model to make counterfactual predictions, I will compare my dollar-valued results to other structural parameters estimated by migration models of sequences of choices. The purpose of this exercise is to both to compare my results to those found by studies with similar empirical implementations and also to discuss where some of the differences I find highlight areas of my model that are not the same as previous works. My points of comparison will be with Kennan and Walker and Bishop, both of whom estimated their models from NLSY79²⁶ data, and Gemici who, like myself, used the PSID.

All of the above models included a "home bonus," in which individuals received a utility benefit from being in their home location. These are defined differently based

²⁶ National Longitudinal Survey of Youth, 1979

on the definition of location and data availability, but all the studies estimated the value of the home bonus to range from about \$10,000 to \$25,000 when normalized to the same inflator I am using. None of the studies used parental location in their analysis. My finding of parents + home on the utility parameters are in this same range, which since parents are usually in the home location makes sense. However, my results indicate that keeping track of parents' location is a good idea when data permits, since they provide the majority of the value in my model that would otherwise be largely attributed to a home bonus.

Another feature I share with the other models is a geographic moving cost. In all cases, this parameter is not strongly interpreted and mostly is included to help match the relative paucity of long-distance moves observed annually. However, the other models I compare to tend to obtain a much higher moving cost than I do, and while it is not a primary coefficient of interest, it is still informative to consider more closely why this occurs. To get a scope for how large this difference is, the previous models discussed in the last two paragraphs all estimate moving costs at somewhere around \$300,000 whereas I find these costs to be around \$10,000.

This difference occurs for two primary reasons, one of which is a technical consequence of a modeling choice I make and the other of which comes from a more substantive theoretical difference. The technical reason is due to my collapsing of all alternative choices besides home or parents' location into a National move choice, which means that my agents make their choices over five to eleven choices rather than fifty states or MSAs as in Bishop or Kennan and Walker, meaning there are less error draws to make a move relatively favorable²⁷ Bishop notes that in her model, the cost of being forced to move in a period is over \$100,000 less if the agent is allowed to move to his most favored choice rather than an arbitrary location. This

²⁷ Gemici uses nine Census regions, but her model is reliant on receiving a single outside job offer at a time which makes it somewhat different than the others in this way. Still, her moving cost is more in line with those papers' than with mine.

interpretation is more comparable to my intuition of choosing to make a national move and then being assigned probabilistically to the best choice among the possible destinations, but even then it makes her moving cost around twenty times higher than mine rather than thirty times higher.

The substantive reason is that my model, unlike the comparison models, incorporates moves across occupations as well as locations. In particular, this is important because my comparison models do not use occupation, and therefore view job match quality (θ in my notation) as permanent to a location spell, whereas I use a location-occupation spell. This has clear consequences for the interpretation of geographic moves. In a model where a bad match can only be reset with a location move, or else a bad match will have lifelong wage consequences, there must be a large countervailing cost in order to rationalize low mobility rates with an apparently strong motive to move. In particular, there may be a large pool of workers who wish to receive the “home bonus” but also face a poor match in their home location which may offset some of the gains, with moving away and then back the only chance to recover the home bonus and shed the poor wage match. In my model, a much less costly (and, in reality as well as the model, a much more common) way to serve the resetting purpose is to make an occupational switch, which removes the need for a very large “catch-all” cost to set against the lower wages that come from poor matches. This allows me to combine the large-scale framework of the models I compare to with the intuition of studies like Corak and Piraino or Kramarz and Skans, which are interested in the local transmission of occupation. While I do not think that the moving costs are a primary coefficient of interest in my model or the models in the literature I build on, what is interesting is that my decrease in moving costs did not correspond to a decrease in parent/home preferences. I view this as support that my preference for parents terms are not serving this catch-all purpose in the model and that their large significance corresponds to actual value for young workers to live

near their parents.

2.6.4 Counterfactuals

Perhaps a more intuitive way to think about the results is in terms of effects each channel have on the main results of the model. I will consider two basic types of counterfactual scenarios. First, I look at expected wages for counterfactual location decisions of individuals to determine how these affect the observed wage gap between those who live near parents or not for the high school and college groups. Next, I look at the effect of shutting down various elements of the model by computing counterfactual decisions. Within the model, I calculate the effect on wages and migration rates.

At the beginning of the paper, I noted that there is a large difference in differences between high school and college graduates' relative wages when leaving near parents or elsewhere. I will use the model to examine the relative importance of three factors in accounting for this differential effect of proximity to parents. In each case, I will change relevant parameters of the model to essentially shut down the impact of one aspect of the model. I use the adjusted parameters to simulate individual location-occupation decisions and compute predicted wages. Then, I compare results from that outcome to Table 2.7. Looking at the MSA section of Table 2.7, I see that high school graduates' wages (for household heads only) are 0.058 higher when in the same MSA as their parents, but college graduates' are 0.109 lower, for a difference in difference of 0.167. In the following counterfactuals, I consider how much of that value can be explained by the tested effect.

A first consideration is what I have termed the networking effect, which is the direct effect of father's occupation intensities and distance on son's wages and occupation transitions. I therefore set these effects to zero and recalculate predicted wages under these conditions. Formally, the coefficients I set to zero are β_{1f} , β_{2f} and

β_{3f} in Equation 2.11 and $\gamma_{7,cog}$, $\gamma_{8,cog}$, $\gamma_{7,mot}$ and $\gamma_{8,mot}$ in Equations 2.12 and 2.13. I find that this lowers log wages for high school graduates by 0.021 when near fathers, accounting for about 13% of the difference in differences from Table 2.7. I interpret this as the contribution of networking effects to the difference in differences of high school and college graduates' wage effects of proximity to parents.

A second consideration is occupation switching costs. I find larger occupation switching costs for college graduates than high school graduates. Occupation switches can be an important part of wage growth for both groups, albeit often for different reasons. Switches tend to improve occupational characteristics for high school graduates more than for college graduates. Within my model, this occurs in part because college graduates are likelier to start in high task intensity occupations, leaving less room to move up the ladder by switching under the process I am using, and also because father's effects on occupation are significant and positive only for cognitive intensity of high school graduates' occupation. On the other hand, the wage equation suggests that occupation tenure interacted with cognitive intensity tends to be more beneficial for high school graduates, meaning college graduates who are not in good occupations or who do not have good matches have less occupation-specific capital to lose and may therefore see especially large gains from switching early in their careers. To determine the relative importance of these features, I re-calculate predicted wages in the scenario in which occupation switching costs (α_5) are zero. Overall, I find free occupation switching to be particularly beneficial for college graduates in the home location, accounting for a total of about 0.03 of the difference in differences for a further 18% of wage effects.

Third, I want to consider that there may be a difference in characteristics between individuals who stay at home and those who move, and what impact that may have on wage differentials. There are a few ways in which people near or not near their parents may differ. They may be different by age, experience, occupation tenure,

ability η and match quality θ , and whether they are likely to live in a high-wage area. Those near parents also have the direct effects of fathers to affect their wages.

In order to even out these factors, I perform the following counterfactual. I compute predicted wages for each individual observed working in my data under the scenario in which they had chosen to make a national move. Enforcing a national move resets occupation tenure and match quality, ensures individuals are not near parents and essentially equalizes geographic wage benefit. Any remaining difference between those who, in actuality, chose to live near parents instead of elsewhere can be attributed to differences in experience and ability. I will jointly consider those factors to be differential selection of movers.

High school graduates who were in their father's location have an expected log wage 0.027 higher after a forced national move than those who do not currently live near their father²⁸, whereas for college graduates the expected wage of those in the same location is 0.018 lower. I interpret this to be the difference in earnings potential between those near and not near parents, whether by experience, ability or current occupational status. The result indicates that among college graduates, those who move away from parents have slightly higher earnings potential, but for high school graduates, the stayers have higher earnings potential. The difference in differences of 0.045 accounts for about 27% of the difference in differences in the groups' overall wage difference by father's location as shown in Table 2.7. I call this result is the differential selection of movers by education group.

These three factors account for a little over half of the differences in outcomes between movers and stayers across education groups. Other factors which may contribute as well include differential preferences for parents, moving costs and geographic wage dispersion. I find preferences for parents and moving costs to be similar in parameter estimates, and so I expect that incentive to be similar across groups.

²⁸ This is only for those whose father is in the data.

However, the difference in base wages across locations is different, and therefore staying near parents or costs to move will be balanced against different wage opportunities.

I can also use counterfactuals to consider effects on migration rates. Earlier in the results section, I put the value of preference to live near parents in dollar terms, but I can alternatively demonstrate the utility value of parents by measuring how much they affect migration. When shutting down preferences for parents entirely in the model, I calculate that college graduates' inter-MSA moving rates would rise from about 13.3% annually among household heads to 19.5%, with a corresponding rise from about 9% to 14% for high school graduates, around a 50% increase in mobility in both cases. These results show how important parents are to internal migration decisions of young workers, and therefore to the overall geographic mobility of the workforce.

2.7 Conclusions and Future Work

In the initial sections of this paper, I examine the basic relationships between father's characteristics and second-generation PSID respondents. One key data feature is that high school graduates who live in the same labor market as their parents tend to have equal or higher wages than those who do not, whereas college graduates in the same location have lower wages. This could be due to differences in ability, preferences for parents, or labor market advantages of parents between education groups. I touch on various literatures that offer partial explanations for this result and show that my basic data is in line with what others have used. In descriptive regressions, I show that interactions of parental location and occupation characteristics correlates with individuals' wage and occupation outcomes. When I use a continuous (Yamaguchi) measure to characterize occupations, I find that cognitive task intensity is strongly and consistently associated with higher wages. Father's cognitive inten-

sity is also associated with higher wages and higher cognitive intensity for the son's occupation. This effect is strongest when father and son share a location, a result which holds at the state or MSA level.

I then move to a model of location and occupation choice to determine the relative importance of potential channels in determining wages. I am interested in direct parental effects on wages of nearby adult children, preferences among those children for living near their parents, and the possible effect that comes from similarity in ability across generations. I find that father's cognitive task intensity has a positive impact on wages and also on own cognitive task intensity for occupation switchers. I find that this impact of fathers, differences in relative ability of migrants, and higher occupational switching costs for college graduates all contribute to the educational difference in relative wages. The utility parameter associated with living near parents is very high but of a similar value for both groups, which means that differential preferences or amounts of non-labor resource sharing are probably not a key reason for this difference. However, these preferences do play a large role in the amount of migration. I estimate that annual internal migration rates would be 50% higher in each education group if parental preferences did not exist.

There are several extensions I would like to pursue in this work. One point of emphasis would be to use the full set of PSID waves, most recently through 2009. I plan to test the sensitivity of the model estimates to restrictions that emulate data available in more recent waves of the PSID. In particular, the most important issues are the loss of information resulting from biennial surveys²⁹ and the presence of only one "PSID-gened" parent³⁰. Provided the results are not overly sensitive to this, or that additional modeling can help correct areas in which the model is sensitive to

²⁹ From 1997-present, survey data is only collected in odd-numbered years.

³⁰ Individuals who are third-generation or higher will have one parent who is not part of a PSID family, and may not be followed upon the death or divorce of their spouse. In this case, I will not have certain information about proximity to parents as I do for second-generation individuals

lack of data, I plan to estimate the model for PSID waves in recent years³¹.

Another area of interest is to extend the family information I use. The primary non co-resident relationship of economic interest in this paper is between parents and adult children, but the genealogical nature of the PSID makes it possible to study other relationships as well. While PSID respondents' spouses families are not tracked, there is some information in some waves about their parents and origins, so there is some scope for studying how in-laws affect location decisions and labor market outcomes compared to parents. There is also the possibility of testing how siblings' occupations and locations affect each other's choices, since the literature has shown evidence siblings may make decisions strategically. With parents' characteristics having been established to matter to young adults both in and out of the labor market, a broader study of the family's role may be warranted.

³¹ As of July 2013, I have preliminary estimates which suggest the model can be adapted to the newer waves and that results are substantiatively similar using recent waves to the historical 1976-93 waves in this paper

2.8 Tables

Table 2.1: Whether Individual Lives in Home MSA

Age Range	<HS Grad	HS Grad	Some Coll	Coll Grad	Overall
18-23	82.5%	87.2%	85.5%	87.2%	86.2%
24-29	78.4%	77.5%	70.4%	53.5%	69.4%
30-35	78.7%	75.2%	68.3%	39.6%	63.1%

Data Source: Author's Calculations, PSID.

Table 2.2: Annual Inter-MSA Move Rates

Age Range	<HS Grad	HS Grad	Some Coll	Coll Grad	Overall
18-23	8.3%	6.8%	8.1%	8.2%	7.6%
24-29	9.9%	8.0%	9.4%	14.8%	10.4%
30-35	3.6%	6.0%	5.9%	9.3%	6.8%

Data Source: Author's Calculations, PSID.

Table 2.3: Inter-MSA Moves by Age 30

Proportion of Individuals Moving Between 18-30					
	< HS Grad	HS Grad	Some Coll	Coll Grad	Overall
% Moved	32.7%	34.1%	34.1%	53.6%	39.9%
Number of Moves (If Any Moves by 30)					
	< HS Grad	HS Grad	Some Coll	Coll Grad	Overall
One	43.6%	35.4%	32.8%	35.3%	35.4%
Two	35.9%	31.0%	41.8%	26.0%	31.8%
Three or More	20.5%	33.5%	25.4%	38.6%	32.8%

Data Source: Author's Calculations, PSID.

Table 2.4: Son's Educational Achievement by Father's Education

Father's Education					
Son's Achievement	< HS Grad	HS Grad	Some Coll	Coll Grad	Overall
< HS Grad	22.0%	6.3%	3.7%	1.0%	9.0%
HS Grad	47.2%	41.3%	30.1%	14.6%	35.3%
Some Coll	19.3%	26.6%	38.5%	24.9%	25.9%
Coll Grad	11.5%	25.9%	27.6%	59.5%	29.7%
Overall	100.0%	100.0%	100.0%	100.0%	100.0%

Data Source: Author's Calculations, PSID.

Table 2.5: Correlations in Cognitive and Motor Task Intensities

	Own Cog	Own Mot	Father's Cog	Father's Mot
Own Cog	1	X	X	X
Own Mot	-0.1931	1	X	X
Father's Cog	0.5805	-0.1094	1	X
Father's Mot	-0.1336	0.4768	-0.2505	1

Data Source: Author's Calculations, PSID.

Table 2.6: Task Intensity Regression Coefficients: Dependent Variable Cognitive Intensity

	HS Grad		Coll Grad	
Location: State				
Father's	-0.0752	***	-0.0395	***
Father's Cog x Diff Loc	0.2636	***	0.3323	***
Father's Cog x Same Loc	0.5545	***	0.4109	***
Father's Mot x Diff Loc	0.3425	***	0.1277	***
Father's Mot x Same Loc	0.1022	***	0.0385	**
Location: MSA				
Father's	-0.0428	**	0.0052	
Father's Cog x Diff Loc	0.3552	***	0.2313	***
Father's Cog x Same Loc	0.5627	***	0.4725	***
Father's Mot x Diff Loc	0.2267	***	0.1237	***
Father's Mot x Same Loc	0.1036	***	-0.0008	

Controls include own motor intensity, marriage/fertility, age, father's education

*, **, *** indicate significance at 10%, 5%, 1% levels

Data Source: Author's Calculations, PSID.

Table 2.7: Wages and Location of Father, Men 18-35

Hourly Inflation-Adjusted Log Wages Household Heads Only				
	< HS	HS Grad	Some Coll	Coll Grad
State				
Same Location	2.414	2.639	2.712	2.832
Diff Location	2.586	2.623	2.789	3.059
Same - Diff	-0.172	0.016	-0.077	-0.227
% in Same Loc	85.4%	84.7%	78.8%	60.8%
MSA				
Same Location	2.415	2.653	2.721	2.857
Diff Location	2.497	2.594	2.740	2.965
Same - Diff	-0.083	0.058	-0.019	-0.109
% in Same Loc	70.6%	72.6%	61.8%	41.2%

Adjustment to 2007 dollars using CPI

Data Source: Author's Calculations, PSID.

Table 2.8: Wage Regression Coefficients, MSA Level

Wage Regression Coefficients: Dependent Var Ln(Wage)				
	HS Grad		Coll Grad	
Model 1 (3.4):				
Father's MSA	-0.0136		-0.1169	***
Model 2 (3.5):				
Father's MSA	-0.0277		-0.1719	***
Cognitive	0.0843	*	0.583	***
Motor	0.0229		-0.1258	***
Model 3 (3.6):				
Father's MSA	0.0049		-0.1995	***
Cognitive	0.0752		0.5528	***
Motor	-0.007		-0.1665	***
Father's Cog	0.159	***	0.23	***
Father's Mot	0.0139		-0.0297	
Model 4 (3.6):				
Father's MSA	0.0996		-0.6906	***
Cognitive	0.0742		0.5458	***
Motor	-0.0093		-0.1458	***
Father's Cog x Diff Loc	0.0636		-0.0508	
Father's Cog x Same Loc	0.1856	***	0.6195	***
Father's Mot x Diff Loc	0.2086	*	-0.0313	
Father's Mot x Same Loc	-0.0491		0.0114	
Model 5 (3.6):				
Father's MSA	0.1278		-0.9441	***
Cognitive	0.0678		0.5646	***
Motor	0.005		-0.1351	**
Father's Cog x Diff Loc	0.0199		-0.1076	
Father's Cog x Same Loc	0.1587	**	0.7315	***
Father's Mot x Diff Loc	0.2112	*	-0.018	
Father's Mot x Same Loc	-0.0268		-0.0193	
Occ. Distance x Diff Loc	0.21	*	-0.132	
Occ. Distance x Same Loc	0.0926		0.2976	***

"Same/Diff Loc as Father" Location are at the level of MSA

*, **, *** indicate significance at 10%, 5%, 1% levels

Data Source: Author's Calculations, PSID.

Table 2.9: Full Model - Wage Coefficients

Wage Coefficients				
	HS		College	
	Coeff.	SE	Coeff.	SE
Cognitive	0.068	0.1218	-0.1604	0.1026
Motor	0.0211	0.1004	0.1731	0.137
Exper*Cog	0.0562	0.0284	0.1577	0.0263
<i>Exper</i> ² *Cog	-0.001	0.0018	-0.007	0.0021
Exper*Mot	0.0343	0.0225	-0.0001	0.0364
<i>Exper</i> ² *Mot	-0.0002	0.0015	0.0018	0.003
Tenure*Cog	0.1533	0.0531	-0.0289	0.0347
<i>Tenure</i> ² *Cog	-0.0393	0.0102	0.0062	0.0058
Tenure*Mot	-0.0098	0.0384	0.1784	0.0517
<i>Tenure</i> ² *Mot	0.015	0.007	-0.0242	0.0088
Exper*Non-Head	0.0096	0.0154	0.2288	0.0255
<i>Exper</i> ² *Non-head	0.0027	0.0014	-0.0151	0.0032
Same Loc*Father's Cog	0.2407	0.0416	-0.0642	0.0397
Same Loc*Father's Mot	-0.169	0.0325	-0.1405	0.0465
Same Loc*F. Occ. Distance	0.1142	0.0396	-0.0714	0.052
θ	0.0564	0.0278	0.1346	0.0355
η_c *Cog	-0.0399	0.0196	0.0556	0.0177
η_m *Mot	-0.0166	0.0184	-0.0748	0.0223
η_c *Non-head	0.0146	0.0931	-0.1576	0.1179
η_m *Non-head	-0.0581	0.1038	0.1031	0.1049

Table 2.10: Full Model - Occ. Transition Coefficients

Occupation Transition Coefficients				
Cognitive Intensity				
	HS		College	
	Coeff.	SE	Coeff.	SE
Constant	0.3856	0.0256	0.5174	0.0279
Prev. Cognitive	0.1327	0.0227	0.2762	0.0285
Prev. Motor	0.0107	0.0267	-0.014	0.0212
Prev. Unemp	0.0066	0.0212	0.166	0.0255
η_c	0.0534	0.0397	-0.0377	0.0225
η_m	-0.0534	0.0463	0.0506	0.0209
Same Loc*Father's Cog	0.1246	0.0289	-0.0527	0.0195
Same Loc*Father's Mot	-0.0868	0.0269	-0.016	0.0217
Motor Intensity				
	HS		College	
	Coeff.	SE	Coeff.	SE
Constant	0.4907	0.0222	0.3155	0.0388
Prev. Cognitive	-0.0529	0.0197	-0.0333	0.0396
Prev. Motor	0.2228	0.0232	0.2518	0.0295
Prev. Unemp	0.1094	0.0184	0.0889	0.0355
η_c	-0.0036	0.0345	0.0327	0.0313
η_m	0.0047	0.0402	-0.0187	0.029
Same Loc*Father's Cog	0.012	0.0251	-0.0406	0.0272
Same Loc*Father's Mot	0.0172	0.0233	0.0342	0.0302

Table 2.11: Full Model - Utility Parameters

	Utility Parameters					
	HS			College		
	Coeff.	SE	\$ value	Coeff.	SE	\$ value
Wage	4.0587	0.0268		4.0396	0.031	
Moving Cost	0.7677	0.0146	4961	0.7814	0.0083	6647
Move*married	0.5746	0.0294	3713	0.4856	0.0173	4131
Move*kids	0.3078	0.0271	1989	0.2122	0.0218	1805
Occ Switching Cost	0.0841	0.0013	543	0.1269	0.0019	1080
Same Loc. As Parent	2.7774	0.059	17947	1.9693	0.0353	16753
Parent*married	-1.1276	0.1033	-7286	-0.6121	0.0705	-5207
Parent*kid	0.1381	0.0918	892	-0.1183	0.08	-1006
Home Location	0.4865	0.0206	3144	0.2014	0.0152	1713
Home*married	0.3348	0.0449	2163	0.2619	0.0344	2228
Home*kids	0.1661	0.0451	1073	0.2694	0.044	2292
Not Working	8.1238	0.1898		8.8803	0.2648	
Non-head	2.4024	0.0399		2.3749	0.1187	
NW*NH	3.6384	0.0103		3.2229	0.0185	

Implied dollar value in 2007 dollars, calculated at mean wages for given education group

Affirmative Action and University Fit: Evidence from Proposition 209

3.1 Introduction

The U.S. Supreme Court recently ruled on the constitutionality of race-based preferences (affirmative action) in university admissions.¹ The Court's ruling hinged on whether the University's admissions policies was a narrowly tailored use of race-based criteria previously established, and did not affirm or overrule the constitutionality of previous decisions, thus making likely that affirmative action will continue to inspire substantial political and social debate. One of the arguments opponents of affirmative action have advanced is that affirmative action actually hurts the individuals it is supposed to help – the *mismatch hypothesis*. According to the mismatch hypothesis, affirmative action in admissions leads to underrepresented minorities being admitted to colleges with entering credentials that are significantly lower than their non-minority counterparts resulting in the minority students not being competitive.²

¹ The Supreme Court heard oral arguments in the case of Fisher v. University of Texas on October 10, 2012 and decided on the case on June 24, 2013.

² See the debate over mismatch effects in law schools in Sander (2004, 2005a, 2005b), Ayres and Brooks (2005), Ho (2005), Chambers et. al. (2005), Barnes (2007) and Rothstein and Yoon (2008).

In this paper we examine the mismatch hypothesis in the context of college graduation rates. As documented in Turner (2004), Bound and Turner (2007, 2011), and Bound, Lovenheim and Turner (2010a), while the number of students attending college has increased over the past three decades in the U.S., college graduation rates (i.e., the fraction of college enrollees that graduate) and college attainment rates (i.e., the fraction of the population with a college degree) have hardly changed since 1970 and the time it takes college students to complete a baccalaureate (BA) degree has increased (Bound, Lovenheim and Turner, 2010b). The disparities between the trends in college attendance and completion or time-to-completion of college degrees is all the more stark given that the earnings premium for a college degree relative to a high school degree nearly doubled over this same period (Goldin and Katz, 2008).

We examine differences in graduation rates and the academic preparation of minority and non-minority students attending the various UC campuses between the years 1995-2000, using a unique source of student-level data that covers the universe of students who applied to one or more of the UC campuses. We obtained these data from the University of California Office of the President, the administrative offices of the entire UC system and refer to them as the “UCOP” data. The UCOP data cover a period where race-based preferences were banned in California. In 1996, the voters of California approved Proposition 209 – Prop 209 hereafter – which stipulates that: “The state shall not discriminate against, or grant preferential treatment to, any individual or group on the basis of race, sex, color, ethnicity, or national origin in the operation of public employment, public education, or public contracting.” The Proposition took effect in 1998.

Using these student-level data, we find evidence that the graduation rates of minorities increased after Prop 209 was implemented. Indeed, the data reveal that under-represented minorities were 4.4 percentage points more likely to graduate in the period after Prop 209 than the period before. We also find that the distribution

of minorities entering the UC system shifted from its more selective campuses (e.g., UC Berkeley and UCLA) towards its less selective ones. Moreover, while there was an overall improvement in the academic preparation of minorities enrolling at UC campuses after Prop 209 went into effect, the greatest improvements occurred at the less-selective campuses. Taken together, this evidence may be consistent with the mismatch hypothesis noted above.

As we argue below, the scope for the mismatch of students to campuses with affirmative action and its alleviation with bans on its use hinges on whether some campuses, presumably less-selective ones, are better-suited to produce positive outcomes, e.g., graduation rates, for less-prepared students while other universities, typically more-selective ones, are better-suited for more-prepared students. In contrast, if more-selective universities were able to produce better outcomes, such as graduation rates, for students of all levels of preparation than less-selective ones, then there is no scope for student-university mismatch. Bans on affirmative action would not be expected to improve the graduation rates of minority students, especially those with weaker backgrounds. We formalize these arguments below, characterizing and estimating graduation production functions for each of the UC campuses and examining whether and how they differ across campuses.

The student-level UCOP data we examine also reveal that after Prop 209 there was a decline in the number of under-represented minorities enrolled at one of the UC campus. And, if the minority students who did not attend a UC campus after Prop 209 were the least prepared, then graduation rates would have likely risen, regardless of the campus they would have attended. That is, Prop 209 may have induced a significant *selection effect* on minority enrollments within the UC system that would provide an alternative explanation to mismatch for why minority graduation rates improved.

To separate the mismatch from the enrollment selection explanations post-Prop

209 minority graduation rate increases, we exploit the richness of the UCOP data on cohorts of students that entered the UC system before and after Prop 209. These data contain measures of high school GPAs and SAT scores and of parental income and education, which allow us to both control for these factors in evaluating the effects of Prop 209 and assess how they influence minority (and non-minority) graduation probabilities at the various UC campuses. The UCOP data provide information not only on which UC campus a student enrolled (as well as whether they graduated from that campus), but also on the other UC campuses to which they applied and the ones to which they were admitted. We use the information on the UC campuses to which students were admitted, and the quality of those UC campuses, to implement a modified version of the method used in Dale and Krueger (2002) to control for student qualifications beyond those measured by high school GPA and test scores.

We decompose the post-Prop 209 change in minority graduation rates into three components: better matching, better students, and a third, residual, category of post-Prop 209 change in graduation rates not accounted for by the matching or selection. We refer to the latter (residual) component as the *university response* to the Prop 209 affirmative action ban.

We find that better matching can explain only 20% of the improvement in minority graduation rates within the UC system. However, this small overall effect, masks two notable phenomena with respect to the potential role of matching. First, we find that matching is much more important in accounting for the graduation gains of students in the bottom of the academic preparedness distribution; moreover, it would have been even larger had minorities been allocated to universities in the same way whites were allocated conditional on academic preparation. Second, as we discuss in the Conclusion, Arcidiacono, Aucejo and Hotz (2012) find that improved matching played a much more prominent role in improved graduation rates of minorities who initially enrolled at UC campuses in STEM (Science, Technology and Engineering)

majors, especially in the higher rates that minorities who started in STEM majors actually graduated with a STEM degree.

We find that the largest share of the increase in minority graduation rates, 35-50%, is due to the changes in student characteristics with Prop 209. But the changes in the characteristics of minority enrollees post-209 are not all in the same direction. While some measures of preparation were higher in the post Prop 209 period (high school grades and SAT scores) other measures actually fell (parental income and parental education). Hence, the pool of minority enrollees actually became more diverse from a socioeconomic perspective.³

Finally, we attribute the remaining 30-45% of the minority graduation gains to the residual category of university response. Below, we present some anecdotal evidence that suggest that universities did indeed respond to Prop 209 by focusing more resources on the retention of their enrolled students, increasing their graduation rates. That such a large share of the gains in graduation result from responses to UC campuses suggests that potential negative effects on minorities from the removal of affirmative action may be over-stated in one important respect: universities may respond to decreased diversity by investing more in the minorities and other students from disadvantaged backgrounds who do enroll.

The remainder of the paper is organized as follows. In Section 3.2 we describe the UCOP data and present the unadjusted levels and post-Prop 209 changes in minority and white student enrollments, measures of their academic preparation and their graduation rates. In Section 3.3 we characterize the mismatch hypothesis for the assignment of minority students to colleges of differing quality and establish the conditions it requires in terms of the differences across colleges in their capacity to produce graduation for students of disparate academic preparation. In Section 3.4

³ This may be a result of the UC system placing more weight on characteristics correlated with race after Prop 209 since they could not explicitly take race into account. See Antonovics, Backes, and Ramey (2012) for a discussion.

we develop and estimate a model of college graduation that embed campus-specific graduation production functions that depend on student preparation and allow for a post-Prop 209 effect. In Section 5 we present the results. Given the estimates of the model, Section 3.6 examines the extent to which Prop 209 increased graduation rates through better matching of students to schools. Section 3.7 decomposes the increased graduation rates following Prop 209, focusing in particular on the roles of better matching, university responses to Proposition 209, and changes in the selection of students who enrolled in the UC system. Section 3.8 concludes.

3.2 Graduation Patterns in the UC System Before and After Prop 209

The data we use were obtained from the University of California Office of the President (UCOP) under a California Public Records Act request. These data contain information on applicants, enrollees and graduates of the UC system. Due to confidentiality concerns, some individual-level information was suppressed. In particular, the UCOP data we were provided have the following limitations:⁴

1. The data are aggregated into three year intervals from 1992-2006.
2. The data provide no information on gender, and race is aggregated into four categories: white, Asian, minority, and other
3. Academic data, such as SAT scores and high school grade point average (GPA), were only provided as categorical variables, rather than the actual scores and GPAs.

Weighed against these limitations is having access to two important pieces of information about the individuals who applied to and possibly enrolled at a UC campus.

⁴ See Antonovics and Sander (2011) for a more detailed discussion of this data set.

First, we have information on every individual who applied to any of the schools in the UC system over the period, including to which campuses they applied and were admitted. As described below, we use the latter information to adapt a strategy used in Dale and Krueger (2002) in order to account for unmeasured student qualifications. Second, we were provided with access to an index of each student's preparation for college, given by the sum of a student's SAT I score, rescaled to be between 0 to 600, and his or her high school GPA, rescaled to be between 0 to 400. Below, we refer to this as a student's high school *Academic Index*. We have data for the entering cohorts in the three years prior to the implementation of Prop 209 (1995, 1996, 1997), and for three years after its passage (1998, 1999, 2000).

In Table 3.1, we present summary statistics for the individual-level UCOP data and its measures of student qualifications by race and for applicants, admits, enrollees and graduates for campuses in the UC system, pre- and post-Prop 209.⁵ The first panel gives the descriptive statistics for under-represented minorities (URMs). As a fraction of the number of minority graduates from California's public high schools,⁶ enrollment rates fell from 4.6% to 3.6%. Conditional on enrolling, minority graduation rates increased by 4.4% off a base rate of 62.4% post-Prop 209.⁷ While the share of white high school graduates who applied, attended, and graduated in the UC system all did not significantly change post-Prop 209 (second panel), graduation

⁵ The corresponding data for Asian American and Other Races (including un-reported) are given in Table B.1 in the appendix.

⁶ The number of California public high school graduates by race and year is given at <http://www.cpec.ca.gov/StudentData/StudentSnapshot.ASP?DataReport=KGrads>. The number of California applicants by race and year can be found at <http://statfinder.ucop.edu>. While not all of the minorities applying to, enrolling at or graduating from UC campuses are from California's public high schools, a large fraction are and we use this benchmark to account for the trends in the numbers of minorities at risk to go to college.

⁷ Graduation rates are measured as graduating in 5 years or less. There are a small number of individuals that are listed as graduating but do not have a graduation time. In the period we analyze, these individuals are almost exclusively listed as having a major classified as 'Other'. We drop these individuals from our sample though are qualitative are unaffected by the treatment of these individuals.

rates conditional on enrolling also showed a significant increase at 2.5%.

With respect to applications at UC campuses before and after Prop 209, while applications by URM students increased, as a share of California public high school graduates, they declined 1.1%. The latter decline suggests the possibility of a chilling effect of Prop 209, where minorities are less likely to apply under the new admissions rules. However, other evidence suggests otherwise. For example, using the same UCOP data as used in this paper, Antonovics and Sander (2012) argue that affirmative resulted in a warming, rather than a chilling, effect, in that minorities, as a group, were more likely to enroll in the UC school conditional on being admitted and Antonovics and Backes (2012) show that the sending of SAT scores by minority applicants to UC campuses did not change post-Prop 209.

With respect to academic preparation as measured by the student's academic index, minorities had much lower scores at each stage of the college process than whites both prior to and after Prop 209 was implemented (Table 3.1). This difference in academic preparation accounts, in part, for the lower proportion of minority high school students being admitted to a UC campus ("Share of Calif. HS Grads") compared to whites. However, after Prop 209 is implemented, the academic preparation of minority applicants, admits, enrollees, and graduates improved, both absolutely and relative to whites. This improvement in academic preparation of the minority students that enrolled at a UC campus after Prop 209 suggests that changes in minority student *selectivity* with respect to academic preparation noted in the Introduction may have accounted for some, if not all, of the improved graduation rates of minorities after the implementation of Prop 209.

But, the change in the selectivity of enrolled minority students with Prop 209 may not have improved uniformly. As shown in Table 3.1, there was a significant and sizable decline in the proportion of minority enrollees and graduates from more "advantaged" family backgrounds after Prop 209 went into effect. Among admitted

Table 3.1: Characteristics of UC Applicants, Admits, and Enrollees Pre-Prop 209 and Post-Prop 209 Change, Under-represented Minorities and Whites[†]

	Applied			Admitted			Enrolled			Graduated		
	Pre-Prop 209	Change	Pre-Prop 209	Prop 209	Change	Pre-Prop 209	Prop 209	Change	Pre-Prop 209	Prop 209	Change	Prop 209
<i>Under-represented Minorities:</i>												
No. of Minorities	30,911	2,511	24,332	-470	13,278	-707	8,198	92	8,198	653.7	12.4***	12.4***
High School Acad. Index	619.7	14.7***	645.7	17.2***	641.5	15.6***	653.7	12.4***	653.7	0.417	-0.046***	-0.046***
Parents have BA	0.369	0.004	0.381	-0.014***	0.385	-0.039***	0.417	0.012	0.417	0.334	0.012	0.012
Parents' Income \leq \$30K	0.379	-0.019***	0.364	-0.008*	0.364	0.008	0.334	-0.018***	0.334	0.238	0.044***	0.044***
Parents' Income \geq \$80K	0.195	0.015***	0.203	0.009**	0.211	-0.010*	0.238	-0.018***	0.238	0.624	0.005*	0.005*
Graduation Rate												
Share of Calif. Public HS Grads	0.107	-0.011***	0.084	-0.016***	0.046	-0.010***	0.028	-0.005*	0.028			
<i>Whites:</i>												
No. of Whites	67,781	8,202	54,480	4,385	27,617	1,945	20,770	2,211	20,770	730.7	12.4***	12.4***
High School Acad. Index	710.4	11.1***	729.8	8.8***	722.6	13.3***	730.7	12.4***	730.7	0.822	-0.008**	-0.008**
Parents have BA	0.801	-0.002	0.813	-0.010***	0.805	-0.008**	0.822	-0.008**	0.822	0.100	-0.006*	-0.006*
Parents' Income \leq \$30K	0.103	-0.008***	0.101	-0.006***	0.109	-0.006***	0.100	-0.006*	0.100	0.540	0.016***	0.016***
Parents' Income \geq \$80K	0.528	0.019***	0.533	0.013***	0.525	0.015***	0.540	0.016***	0.540	0.769	0.025***	0.025***
Graduation Rate												
Share of Calif. Public HS Grads	0.187	0.003	0.150	-0.003	0.076	-0.002	0.057	0.000	0.057			

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Data Source: UCOP individual data, Pre-Prop 209 (1995-97); Post-Prop 209 (1998-2000).

Variables: *No. of Observations* is the total number of students who engaged in activity indicated in column heading; *No. of Obs./No. of HS Grads* is ratio of a column's No. of Observations to the number of public high school graduates per year in California; *Graduation Rate* is share of enrolled students that graduated in 5 years or less; *High School Acad. Index* is sum of re-scaled student's SAT I score (0 to 600 scale) plus re-scaled student's UC-adjusted high school GPA (0 to 400 scale); *Parents have BA* is indicator variable of whether student has at least one parent with Bachelor Degree or more; *Parents' Income \leq \$30K* is indicator variable for whether parents' annual income is \leq \$30,000, where Pre-Prop 209 income are inflation-adjusted to Post-Prop 209 levels; *Parents' Income \geq \$80K* is corresponding variable whether parents' annual income is \geq \$80,000; and where *Graduated* denotes those who graduated in 5 years or less.

[†] Descriptive statistics for Asian Americans and Others (including Unknowns) are omitted from table, but are available in the appendix.

minorities who actually enrolled at a UC campus, there was an 0.039 reduction (a 10% decline) in the proportion with parents who had a BA degree and a corresponding 0.046 reduction (an 11% decline) among those minorities that graduated from a UC campus after Prop 209 was implemented. Similarly, post-Prop 209 a greater share of applicants and admits had parents with incomes above \$80,000. Yet, the share of enrollees whose parental income was greater than \$80,000 *fell*. That is, while minorities from more advantaged family backgrounds continued to apply and be admitted to UC campuses after Prop 209 (though the set of UC campuses where they were admitted may have changed), they were less likely to enroll at one of the campuses and less likely to graduate from one of them.⁸ This decline in minority students from more advantaged backgrounds that enrolled at UC campuses after Prop 209 would seem to work against improved graduation rates, given previous findings that students from wealthier and better educated parents do better in college.⁹

We next consider how graduation rates and academic preparation varied across UC campuses before and after Prop 209. Table 3.2 gives the distribution of both for minorities and whites, respectively. The campuses are listed in order of their *U.S. News & World Report* ranking as of the fall of 1997.¹⁰ We use this ranking throughout our study as our measure of the selectivity and/or quality of the UC campuses. Focusing initially on the pre-Prop 209 tabulations, one sees that the academic index

⁸ We are unable to determine whether, after Prop 209, these more advantaged minorities who applied and were accepted to a UC campus went to colleges not subject to Prop 209, i.e., private colleges in California or public or private colleges outside of the state. But we doubt that they disproportionately ended up at less-selective public colleges in the state, i.e., at CSU campuses or one of California's community colleges, or not attending college.

⁹ For example, Turner (2005) finds that students of mothers with a college degree have a 14 percentage point higher probability of attaining a BA degree than do students whose mothers do not.

¹⁰ The 1997 *U.S. News & World Report* rankings of National Universities are based on 1996-97 data, the academic year before Prop 209 went into effect. The rankings of the various campuses were: UC Berkeley (27); UCLA (31); UC San Diego (34); UC Irvine (37); UC Davis (40); UC Santa Barbara (47); UC Santa Cruz (NR); and UC Riverside (NR).

and graduation rates are systematically related to the rankings of UC campuses, with more-selective campuses having students that are better prepared and more likely to graduate. This is true for minorities and for whites. And, consistent with the tabulations in Table 3.1, whites have higher academic indices and graduation rates than do minorities, a pattern that holds campus-by-campus.

The *changes* in student preparedness and graduation rates post-Prop 209 are not ordered according to the selectivity of the various campuses (Table 3.2). For example, UC Santa Barbara had the largest post-Prop 209 improvements in student academic preparedness and graduation rates, even though it ranked sixth out of the eight UC campuses in the *U.S. News & World Report* rankings. Furthermore, UC Berkeley and UC Riverside, which were the top and bottom ranked UC campuses, were both in the bottom third of post-Prop 209 gains in minority academic preparedness and graduation rates.

Taken together, the across-campus changes that occur in minority graduation rates and the academic preparation of those minorities that do enroll is potentially consistent with the view that the Prop 209 ban of affirmative action resulted in minority students being *better matched* to campuses based on their academic preparation. But as noted earlier, this improvement also may be consistent with greater selectivity in UC minority enrollments post-Prop 209. In order to sort of these factors, we provide, in the next section, a more precise characterization of the conditions required for better matching when affirmative action in the admission process is banned and, in the following section, a strategy for isolating these matching and post-Prop 209 effects from selectivity in enrollments.

Table 3.2: High School Academic Index and College Graduation Rates by UC campus for Minorities & Whites, Pre Post Prop 209 & Change Post Prop 209

Campus [‡]	Under-represented						Whites					
	Minorities											
	Acad. Index		Grad. Rate		Acad. Index		Grad. Rate		Acad. Index		Grad. Rate	
	Pre	Prop 209	Pre	Prop 209	Pre	Prop 209	Pre	Prop 209	Pre	Prop 209	Pre	Prop 209
	Change		Change		Change		Change		Change		Change	
UC Berkeley	679	15	0.675	0.030	794	5	0.847	0.026				
UC UCLA	674	29	0.656	0.057	766	19	0.839	0.036				
UC San Diego	681	41	0.661	0.061	760	13	0.826	-0.005				
UC Irvine	621	33	0.626	0.039	693	8	0.685	0.047				
UC Davis	637	12	0.540	0.091	721	2	0.776	0.009				
UC Santa Barbara	605	44	0.599	0.104	682	35	0.743	0.054				
UC Santa Cruz	590	29	0.598	0.044	683	4	0.688	0.033				
UC Riverside	582	14	0.583	0.005	669	-1	0.636	-0.014				

Data Source: UCOP.

[‡] Campuses are listed in order of their ranking in the 1997 *U.S. News & World Report* Top 50 National Universities.

3.3 The Mismatch Hypothesis and University Graduation Production Functions

In this section, we characterize the mismatch hypothesis as it applies to minority graduation rates. To fix ideas, consider the following characterization of the *graduation production function* for one of the UC campuses. Let $P_j^g(AI)$ denote the graduation rate that campus j can produce for a minority student with an academic preparation index of AI . For simplicity, assume that this production function is linear and increasing in AI , i.e.,

$$P_j^g(AI) = \phi_{0j} + \phi_{1j}AI \quad (3.1)$$

for UC campus $j, j = 1, \dots, J$, where $\phi_{1j} > 0$.

One could proceed by specifying the admission criteria of campuses in the presence and absence of affirmative action, characterizing the criteria students have for the campuses to which they apply and to which they enroll if admitted and that campuses use in its admission decisions and, thus, the matching of students to colleges (or alternative activities).¹¹ For the purposes of assessing the mismatch hypothesis, it is sufficient to assume that relative to an affirmative action regime, a college under an affirmative action ban will place less (or no) weight on the diversity of an incoming student body and more weight on selecting students based on their academic preparation or AI . The mismatch hypothesis asserts that, under affirmative action, minority students are more likely to be matched to higher quality colleges for which they are less well-prepared than their non-minority counterparts. By banning affirmative action, this form of mismatch of minority students will be reduced, i.e., minority students will be “better matched” to colleges on the basis of their academic preparation (AI), and the outcomes of minorities, such as their graduation rates,

¹¹ See Eppele, Romano and Sieg (2008) for such an equilibrium model of college admissions under affirmative action and when it is banned.

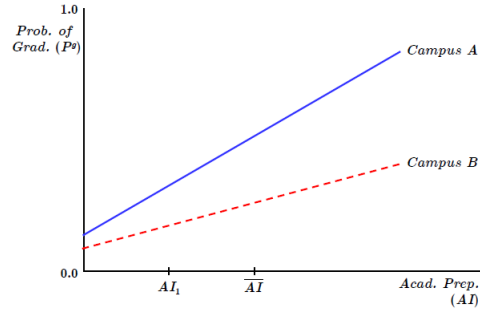
will improve.¹²

The validity of this mismatch explanation hinges on whether colleges differ in their graduation production functions and how they differ between high-quality (more selective) and lower quality (less selective) colleges. To see this, consider Figure 1, which illustrates two possibilities for the relationship between the production functions of a more-selective college, *Campus A*, and a less-selective one, *Campus B*. Panel (a) illustrates the case where Campus A has an *absolute advantage* over Campus B in producing higher graduation rates for students of *all* levels of academic preparation (AI). At the same time, the way Panel (a) is drawn, the higher quality campus, A, has a comparative advantage at producing higher graduation rates among better prepared students than Campus B. This latter assumption provides a motivation for why better prepared students tend to attend higher quality colleges.

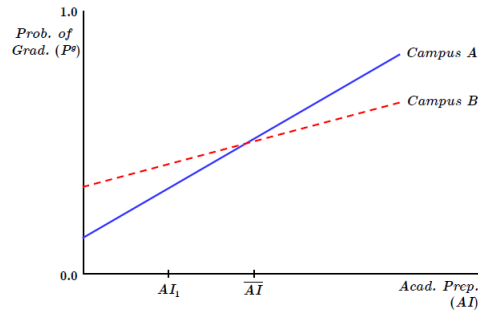
For the predictions of the mismatch hypothesis to hold, one requires a stronger set of differences between the production functions of higher- and lower-quality campuses. To see this, consider Panel (b) of Figure 1. As before, Campus A has a comparative advantage in graduating better prepared students. Now, however, Campus A only has an absolute advantage in the production of graduations for better prepared students, i.e., only for $AI > \overline{AI}$. And, Campus B now has an absolute advantage in the production of graduations for less-prepared students ($AI < \overline{AI}$). Now consider what happens to a minority student with academic preparation AI_1 who was admitted and attended Campus A under affirmative action but is no longer able to get into Campus A once affirmative action is banned.¹³ Because it has an absolute advantage in graduating less prepared students, this student's likelihood

¹² See Dillon and Smith (2009) for reasons why students end up over-matched or under-matched.

¹³ If students know their academic preparation then they would presumably internalize the fact that their graduation rates are lower at the more selective campus. However, as discussed in Arcidiacono, Aucejo, Fang, and Spenner (2011), when schools have private information on the probability of success, it is possible for minority students to be made worse off under affirmative action.



(a) Campus A has **absolute advantage** in graduations over Campus B for **all** levels of AI



(b) Campus A **better** than Campus B at graduating **better prepared** students ($AI > \overline{AI}$) but B **better** than A for **less prepared** ones ($AI < \overline{AI}$)

FIGURE 1: Alternative Relationships between Graduation Production Functions of Higher Quality and Lower Quality Campuses

of graduating from college increases by enrolling in Campus B, as the mismatch hypothesis predicted.¹⁴

As the above discussion makes clear, the mismatch hypothesis requires lower-quality (less selective) universities to have an absolute advantage, and not just a comparative advantage, in graduating less academically prepared minority students.

¹⁴ Campus B having a comparative, but not absolute, advantage over A with respect to graduations among less prepared students, as in Panel (a) of Figure 1, is not enough to generate the implications of the mismatch hypothesis. To see this, note that if higher quality colleges have an absolute advantage in graduating all students as in Panel (a), then a less prepared minority student with AI_1 ($AI_1 < \overline{AI}$) that was admitted to Campus A under affirmative action will experience a *lower*, rather than *higher*, graduation rate after affirmative action is banned and she can no longer attend Campus A.

Below, we estimate campus-specific graduation production functions for each of the UC campuses and assess whether this condition holds across the UC system's higher and lower ranked campuses.

Before discussing our estimation strategy, several caveats and comments are in order. First, our claims about what is required about the graduation production functions of more and less selective campuses/colleges for the mismatch hypothesis to hold does not characterize how the admission and enrollment processes of students will change after affirmative action bans like Prop 209. As noted in Section 3.2, the number and composition of minority student enrolled at UC campuses changed with Prop 209. Presumably, a complete model of admission and enrollment *selection processes* would be required to characterize these outcomes. In what follows, we do not specify or estimate an explicit model, but we do develop strategies to correct for selection effects associated with the Prop 209 ban.

Second, it is possible that affirmative action bans also may affect what colleges do with respect to the graduation rates of minority and non-minority students. For example, colleges subject to affirmative action bans may try to improve their tutoring and counseling programs especially at freshman in order to help them get through their first year of collegiate studies in order to reduce the rates of drop-out and improve graduation rates.

There is anecdotal evidence that UC campuses did take actions after Prop 209 to improve student retention rates. For example, UCLA changed the way its introductory courses for first year students were organized in the wake of Prop 209 in an attempt to improve the retention of "disadvantaged students."¹⁵ While some of these efforts were direct responses to the passage of Prop 209, others appear to have been in response to the rising (and continuing) attention to retaining college

¹⁵ See "Intercollegiate Forums at UCLA discuss Retention of Minorities," *Daily Bruin*, March 2, 1998.

enrollees, especially those from disadvantaged groups.¹⁶ We note that the efforts by UC campuses to improve outreach and retention of minority students after Prop 209 could not directly target racial and ethnic groups, which was deemed a violation of ban on the use of race and ethnicity “in the operation of ... public education” (Text of Proposition 209).¹⁷ This led to a restructuring of official campus programs to target disadvantaged, rather than only minority, students based on “academic profiles, personal backgrounds and social and environmental barriers that may affect [a student’s] university experience, retention and graduation.”¹⁸ As a result, some of these retention efforts in response to, or coincident with, Prop 209 may affect the graduation rates of minority and non-minority students.

In the empirical analyses presented below we allow for post-Prop 209 changes in graduation rates at UC campuses, net of changes in selectivity in student enrollments and campus-specific graduation production functions. We examine the extent to which such changes occurred not just among minorities but also among non-minorities. The latter effects might be expected to the extent that efforts to improve retention and graduation rates were not (or could not be) targeted exclusively to minorities. We refer to these effects as the “university response,” although it is really a residual effect since we are not able to directly quantify or characterize the programs that were put in place to improve retentions after the passage of the ban.

3.4 Estimating Graduation Production Functions and the Post-Prop 209 Effect on Graduations

In order to assess the role of mismatch, selection and any post-Prop 209 response

¹⁶ See “Scholars urge Early Help for Minorities,” *UCLA Today*, March 16, 1998.

¹⁷ See “Prop. 209 Mandates Changes on Campus,” *UCLA Today*, October 10, 1997. As noted in Horn and Flores (2003), some of the post-Prop 209 efforts to improve the retention of minority enrollees at UC Berkeley were handled by student-run organizations who were not directly subject this provision of Prop 209.

¹⁸ “Prop. 209 Mandates Changes on Campus,” *UCLA Today*, October 10, 1997.

by UC campuses to improve graduation rates, we specify and estimate models of college graduation. In the discussion below, we focus on minority students, although we later present estimates for corresponding models estimated for whites and Asian Americans.

Our interest focuses on estimating the parameters of the campus-specific production functions in (3.1) and any post-Prop 209 additional change in minority graduation rates among enrollees, net of the post-Prop 209 changes in the admissions and enrollment processes that were manifested in the changing characteristics of minority students seen in Table 3.1. As before, the probability i in cohort t graduates from institution j is specified as depending on the student's academic preparation. We now extend the model from the previous section to also allow the probability of graduating to depend on her family background characteristics, X_{it} , to capture, for example, financial constraints and preferences, and whether the individual was a part of the post-Prop 209 cohort, $POST_{it}$, to capture factors such as the response by universities to Prop-209. Let G_{ijt} denote the 0/1 indicator of whether minority student i who enrolled at UC campus j in cohort t graduated. We then specify G_{ijt} as:

$$\begin{aligned} G_{ijt} &= P_j^g(AI_{it}, POST_{it}, X_{it}) + \zeta_{it} \\ &= \phi_{0j} + \phi_{1j}AI_{it} + \phi_2POST_{it} + \phi_3X_{it} + \zeta_{it} \end{aligned} \quad (3.2)$$

where ζ_{it} is an error term that captures unobserved (to the econometrician) student preferences and characteristics and where ϕ_{0j} and ϕ_{1j} are the parameters of the campus-specific production function in (3.1).¹⁹

Ideally, a student's unobserved preferences and characteristics captured by ζ_{it} would be independent from which campus they attended, whether they were enrolled

¹⁹ We maintain the linear probability model specification in (3.2) to model graduation rates throughout.

in a pre- or post-Prop 209 entry cohort, their AI and their family background, X . If so, the parameters in linear probability model in (3.2) would be consistently estimated using standard regression methods. But some of a student's unobserved characteristics are likely to correlated with the quality/selectivity of the campus they attend. As has been noted in the literature,²⁰ failure to control for the full set of factors will likely to result in biased estimates of the effects of attending more-selective colleges on the outcomes of interest. To help mitigate this source of selection bias, we implement a modified version of the selection correction method of Dale and Krueger (2002), using information in the UCOP data on the selectivity of the UC campuses to which students were admitted as a proxy for their unmeasured qualifications for college.

Following Dale and Krueger (2002), we construct the following set of indicator variables that measure the selectivity of the UC campuses to which a given student was admitted. Using the *U.S. News & World Report* Top 50 University rankings for 1997, we array the UC campuses from highest ranked to lowest ranked.²¹ The first indicator, a_{i1t} is set equal to 1 for all students that were admitted at UC Berkeley (the top ranked campus) and 0 otherwise. The second indicator, a_{i2t} is set equal to 1 for all students that were admitted to UC Berkeley and/or UCLA (the second ranked school), and we proceed in this way until we define the final indicator, $a_{i,J-1,t}$, which is set equal to 1 if a student was admitted to at least one of the UC campuses ranked higher than or equal to UC Santa Cruz, the second-lowest ranked campus in the UC system at the time in 1997. We add these these controls variables to the

²⁰ See, for example, Black, Daniel, and Smith (2001), Dale and Krueger (2002), Black and Smith (2004), and Hoxby (2009).

²¹ Recall that these rankings were (with a campus's rank in parentheses): UC Berkeley (27); UCLA (31); UC San Diego (34); UC Irvine (37); UC Davis (40); UC Santa Barbara (47); UC Santa Cruz (NR); and UC Riverside (NR).

specification in (3.2) to obtain:

$$G_{ijt} = \phi_{0j}^* + \phi_{1j}^* AI_{it} + \phi_2^* POST_{it} + \phi_3^* X_{it} + \sum_{k=1}^{J-1} \phi_{4k}^* a_{ikt} + \zeta_{it}^* \quad (3.3)$$

We refer to (3.3) as our *Baseline Specification*.

While accounting for selection on unobservables based on the application of Dale-Krueger in (3.3) may produce unbiased estimates of the campus-specific production function parameters, $(\phi_{0j}^*, \phi_{1j}^*)$, the resulting estimate of the direct effect of Prop 209 on graduation rates, ϕ_2^* , is likely to be biased for the following reason. Unlike the case considered in Dale and Krueger (2002), the admissions processes of campuses were required to change under Prop 209. In particular, Prop 209 required that a person's race or ethnicity could no longer be used as a criteria for admission at any UC campus. As a result, the probability that a minority applicant with a given set of credentials was admitted to a UC campus, especially highly selective ones, was likely to have changed with the implementation of Prop 209. Based on the selectivity of the UC campuses to which a minority was admitted measured by a_{it} , it will appear as though minorities pre-Prop 209 were stronger than those post-Prop 209 because more minorities were admitted to the more-selective UC campuses based on their race/ethnicity prior to Prop 209 than after it was implemented.

To account for the change in UC admission criteria with Prop 209, we adjust the Dale and Krueger (2002) method in the following way. First, we run the regression in (3.3) and retrieve the Dale and Krueger "index" of college preparedness, $\sum_{k=1}^{J-1} \hat{\phi}_{4k}^* a_{ikt}$, for each student that was accepted at a UC campus. We then regress these indices on student's academic index, AI_{it} , family background characteristics, X_{it} , and the dummy indicator of whether the student applied in the post-Prop 209 period:

$$\sum_{k=1}^{J-1} \hat{\phi}_{4k}^* a_{ikt} = \theta_0 + \theta_1 POST_{it} + \theta_2 AI_{it} + \theta_3 X_{it} + \eta_{it} \quad (3.4)$$

It follows that our estimate of the response by universities to Prop 209 is given by:

$$\ddot{\phi}_2^* = \hat{\phi}_2^* + \hat{\theta}_1 POST_{it}. \quad (3.5)$$

We expect $\hat{\theta}_1$ to be negative, as we anticipate that failure to make this adjustment for post-Prop 209 differences in selection procedures, we would tend to overestimate the response by universities to Prop 209. We refer to the above adjustment of the Baseline Specification as selection adjustment *Method 1*.

The adjustment in (3.5) may still be biased upward because less minorities were admitted to *any* UC campus after Prop 209, implying the set of admits in the post-period would be on average stronger (beyond observables) than those in the pre-period. To adjust for this, we throw out pre-period individuals in the bottom 7% of the $\sum_{k=1}^{J-1} \hat{\phi}_{4k}^* a_{ikt}$ distribution, which roughly corresponds to the drop in minorities admitted to any campus in the post period. We then re-estimate (3.4) and calculate again the adjustment given in (3.5). We refer to this second adjustment of the Baseline Specification as selection adjustment *Method 2*. Note that neither of these adjustments of the coefficient on *POST* affects the estimates of the other coefficients.

3.5 Results

Parameter estimates for the Baseline Specification in (3.3) for under-represented minorities (URM), whites and Asian Americans are presented in Table B.2 in the Appendix. To focus attention on the heterogeneity across schools, we re-display the UC campus-specific graduation production function parameters estimates for minorities in Table 3.3. All coefficients are expressed relative to those for UC Riverside. Based on these estimates, we can decisively reject that all of the UC campuses have the same intercept for minorities (i.e., that $\phi_{0j}^* = 0 \ \forall j$) or the same rates of converting the academic preparation into graduation (i.e., that $\phi_{1j}^* = 0 \ \forall j$). The relative magnitudes of ϕ_{0j}^* s and ϕ_{1j}^* s across the UC campuses also are correlated with their degree of selectivity. The correlation coefficient for the institution-specific slopes with

Table 3.3: Parameters Estimates for UC Campus-Specific Graduation Production Functions for Minorities[†]

Campus	Intercept	Academic Index [§]
UC Berkeley	-0.405*** (0.086)	0.538*** (0.129)
UCLA	-0.547*** (0.089)	0.766*** (0.133)
UC San Diego	-0.291** (0.123)	0.413** (0.178)
UC Davis	-0.553*** (0.093)	0.722*** (0.144)
UC Irvine	-0.198* (0.104)	0.282* (0.162)
UC Santa Barbara	-0.136 (0.090)	0.236* (0.142)
UC Santa Cruz	0.010 (0.093)	-0.024 (0.149)

Data Source: UCOP. $N = 23,177$.

[†] See equation (3.1) for specification of graduation production function. The intercepts and slope coefficients are measured relative to those for the UC Riverside, the lowest ranked UC campus.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

the average minority academic index in the pre-period is 0.72, suggesting that more (less) selective schools have a *comparative* advantage in graduating better (worse) prepared students. In contrast, the correlation coefficient for the institution-specific intercepts and the average minority academic index is -0.72.

To illustrate the student-campus sorting implied by the estimates in Table 3.3, we use the parameter estimates in Table 3.3 to predict campus-specific graduation probabilities for minority students from different parts of the academic index distribution. More formally, we use the parameter estimates for the baseline estimating equation in (3.3) to predict graduation probabilities for hypothetical student h with

academic preparation AI_s in the pre-Prop 209 period:

$$P_j^{g*}(AI_s, X_h, POST_h, \hat{\phi}^*) = \hat{\phi}_{0j}^* + \hat{\phi}_{1j}^* AI_s + \hat{\phi}_2^* POST_h + \hat{\phi}_3^* X_h + \sum_{k=1}^{J-1} \hat{\phi}_{4k}^* a_{hk} \quad (3.6)$$

where AI_s is the cutoff value for s th percentile of the minority distribution of A , and where these probabilities were evaluated for each UC campus $k = 1, \dots, J$, for various values of AI_s . Here, we set the values of X_h to the averages for minority enrollees in pre-Prop 209 period.²² The rankings of the UC campuses for each percentile are based on the means of the predicted graduation rates based on (3.6) evaluated at corresponding values of AI_s .

The rankings of UC campuses by their predicted minority graduation rates are displayed in Table 3.4. Several patterns emerge from this Table. First, the rankings of campuses in terms of their graduation rate productivity differ across the academic index distribution. (This is consistent with the across-campus differences in the estimates of ϕ_{1j} s and ϕ_{3j} s in Table 3.3.) Second, some of the UC campuses appear to have an *absolute advantage* (or disadvantage) in producing high graduation rates across the whole distribution of student preparedness. For example, UC Santa Barbara is predicted to produce among the highest, if not the highest, minority graduation rates at each part of the academic index distribution, whereas, UC Davis is predicted to the lowest, or near the lowest, graduation rates at each level of academic preparation. At the same time, most of the rest of the campuses exhibit an absolute advantage in minority graduations for some parts of the preparation distribution but not others. (Recall that absolute differences among campuses in the production of graduations for students at different parts of the preparation distribution is a necessary condition for the mismatch hypothesis.) For example, UCLA, the second-most selective

²² Note that since our estimating equation is linear, the relative rankings of the campuses will not change if we instead considered the post-Prop 209 period or varied the values of the family background characteristics.

UC campus, is predicted to produce relatively low graduation rates for less-prepared students but is one of the best campuses at producing high graduation rates among the best-prepared minorities. In contrast, UC Santa Cruz and UC Riverside, the two least-selective UC campuses, perform well in graduating less-prepared minorities but not better-prepared ones.

Table 3.4 also makes clear that heterogeneity in graduation rates across universities is particularly large for those at the bottom of the distribution. The gap between the highest and lowest graduation rates across schools for students at the 10th percentile of the academic index was over 16 percentage points. For students at the 75th percentile of the academic index, the gap between the highest and lowest graduation rates across schools was less than half that at 7.1 percentage points.

With the estimates of (3.3) and making the corresponding adjustments given by Method 1 and Method 2, we can calculate the effect of Proposition 209 beyond that due to selection and changes in the matching of students to schools. Table 3.5 gives the estimates of the coefficient on *POST*, both under the Baseline Specification and with the corrections outlined in Methods 1 and 2, respectively. Without adjustments, we see that while these net effects are statistically significant for minorities and whites, their values – 4.0% for URMs and 2.3% for whites – are not much different from the unadjusted estimates in Table 3.1. However, when we further adjust for the consequences that Prop 209 had on UC admissions criteria, these estimates fall. Under Method 1 we assume that the pre-Prop 209 admits had the same distribution of unobservables as the post-Prop 209 admits. We find that the direct effect of enrolling in the post-Prop 209 period on graduation rates was 2 percentage points for minorities and 1.5 percentage points for whites. Since the evidence in Table 3.1 clearly indicates that some minorities would not be admitted to any campus post Proposition 209, Method 2 further drops the bottom 7% of minority admits in the pre-Prop 209 period when calculating the adjustment to the *POST* coefficient.

Table 3.4: Rankings of UC Schools by Predicted Graduation Rates at Various Percentiles of the High School Academic Index Percentiles based on Minority Coefficients Estimates[†]

Percentile of the Minority Academic Index				
10th	25th	50th	75th	95th
Riverside (0.613)	Santa Barbara (0.631)	Santa Barbara (0.666)	Santa Barbara (0.702)	UCLA (0.763)
Santa Cruz (0.610)	Riverside (0.631)	Riverside (0.651)	Irvine (0.673)	Santa Barbara (0.753)
Santa Barbara (0.601)	Santa Cruz (0.627)	Santa Cruz (0.645)	San Diego (0.672)	San Diego (0.739)
Irvine (0.563)	Irvine (0.596)	Irvine (0.633)	Riverside (0.672)	Irvine (0.727)
San Diego (0.539)	San Diego (0.579)	San Diego (0.625)	UCLA (0.665)	Berkeley (0.723)
Berkeley (0.490)	Berkeley (0.536)	UCLA (0.595)	Santa Cruz (0.665)	Davis (0.722)
UCLA (0.468)	UCLA (0.527)	Berkeley (0.590)	Berkeley (0.646)	Riverside (0.701)
Davis (0.439)	Davis (0.495)	Davis (0.560)	Davis (0.628)	Santa Cruz (0.692)

Data Source: UCOP.

[†] Average predicted graduation probabilities in parentheses. The predicted probabilities were formed using the estimated coefficients for specification (3.6) for minorities and were predicted using the characteristics of minority students that enrolled at one of the UC campuses in the years 1995-1998.

Table 3.5: Adjusted Post-Proposition 209 Effects

	Coeff	Standard Error
<i>Unadjusted</i>		
Minority	0.040***	(0.006)
White	0.023***	(0.004)
Asian	0.032***	(0.004)
<i>Adjusted</i>		
Minority (Method 1)	0.020***	(0.006)
Minority (Method 2)	0.013*	(0.007)
White	0.015***	(0.004)
Asian	0.024***	(0.004)
Data Source: UCOP.		
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.		

Under Method 2, the effect falls to 1.3 percentage points for minorities, which is still substantial. Complementing the anecdotal evidence given in Section 3.3, these results are consistent with campuses within the UC system responding to Prop 209 by providing more resources to help retain and facilitate higher graduation rates of those students who did enroll after the ban went into effect. As we noted in Section 3.3, the campuses did undertake such efforts and our findings are suggestive that they had a positive effect on minority, and non-minority, graduation rates.

3.6 Did Re-Allocating Students across Campuses Improve Minority Graduation Rates?

As documented in the preceding section, UC campuses differed in their “productivity” of graduating students from differing academic backgrounds. Moreover, it appears that less-selective campuses had either an absolute advantage in producing higher graduation rates for all students or for less prepared students, with the latter being a necessary condition for mismatch. So, to what extent were these Prop

209 gains in minority graduation rates the result of better student-campus matching based on academic preparation that many proponents of banning the use of affirmative action in college admissions claim will result from such bans? And, more generally, to what extent can re-allocating students across campuses improve minority graduation rates?

3.6.1 Alternative Assignment Rules

In this section we attempt to provide partial answers to these questions. We do so by examining the consequences for minority graduation rates from using several “rules” for allocating, or assigning, students across the UC campuses. The assignment rules we consider either capture how minorities (and non-minorities) were allocated across the UC campuses under Prop 209 or provide a quantitative benchmark for how much student-campus matching on academic preparation could have changed minority graduation rates. To avoid confounding the effect of re-allocating students across campuses with those from changes in the composition of minority enrollees that occurred with Prop 209, we use the same “population” of minority students, namely those who enrolled at a UC campus prior to Prop 209, calculating the campus assignments and implied graduation rates under each rule.

We consider the following three rules for assigning minority students across the UC campuses:

AR1: Assign students to the campus that maximizes their probability of graduating

AR2: Assign students to campuses following (implicit) rule used to assign minorities post-Prop 209

AR3: Assign students to campuses following (implicit) rule used to assign whites post-Prop 209

The first assignment rule (AR1) focuses exclusively on achieving high graduation rates, providing the benchmark for the potential impact of student-campus matching on academic preparation. To operationalize AR1, we use the predicted grad-

uation probabilities for minority student h given in (3.6) to assign her to that UC campus that yields the highest probability that she will graduate. Let that school be denoted by j^{max} , and the graduation probability associated with it is $P_{j^{max}}^{g*}(AI_s, X_h, POST_h, \hat{\phi}^*)$. As noted above, we evaluate these graduation probabilities for the sample of pre-Prop 209 ($POST = 0$) minority UC enrollees.

The second assignment rule, AR2, characterizes how minorities were allocated across the UC campuses after Prop 209 went into effect. We also investigate a third assignment rule (AR3) that characterizes what would have happened to minority graduation rates if minority students had been allocated across the UC campuses as whites were after Prop 209. While Prop 209 stipulated that California's public universities could not use race or ethnicity as a criteria for admission, this does not imply that the post-Prop 209 across-campus assignment rules for the *enrollment* of minorities and whites will necessarily be the same. Minorities and whites may have differed in their preferences for attending a particular campus and/or differed in their in-state private and out-of-state college alternatives. Furthermore, in contrast to AR1, neither AR2 or AR3 is insured, by design, to improve the graduation rates of enrolled students. Comparing the results for AR2 and AR3 helps one assess the importance these other factors might play in minority graduation rates.

To operationalize AR2 and AR3, we estimated a multinomial logit model of the UC campus that students actually attended for each of two samples: post-Prop 209 minority UC enrollees for AR2 and post-Prop 209 white UC enrollees for AR3. The probability of choosing a given campus is a function of the same measures of student academic preparedness, AI , and family background, X , used in the estimation of the campus-specific graduation model presented above. Let $\hat{\pi}^{ARn}$, $n = 2, 3$, denote the estimated parameter vectors for the UC campus enrollment models for the samples corresponding to assignment rules AR2 and AR3, respectively. The predicted probability of being assigned to UC campus j under assignment rule AR n is given

by:

$$P_j^a(AI_h, X_h, \hat{\pi}^{ARn}) = \frac{\exp(AI_h \hat{\pi}_{1j}^{ARn} + X_h \hat{\pi}_{2j}^{ARn})}{\sum_{k=1}^J \exp(AI_h \hat{\pi}_{1k}^{ARn} + X_h \hat{\pi}_{2k}^{ARn})} \quad (3.7)$$

for $n = 2, 3$. As with the graduation probabilities evaluated under AR1, we evaluate these assignment probabilities at the characteristics of the pre-Prop 209 UC minority enrollees. Finally, the graduation probabilities associated with these two assignment rules are weighted averages of the predicted graduation probabilities for the UC campuses, using the rule-specific assignment probabilities in (3.7) as weights, i.e.:

$$P_{ARn}^{g*}(AI_h, X_h, POST_h, \hat{\phi}, \hat{\pi}^{ARn}) \equiv \sum_{k=1}^J P_k^g(AI_h, X_h, \hat{\Gamma}_h, POST_h, \hat{\phi}) P_k^a(AI_h, X_h, \hat{\pi}^{ARn}) \quad (3.8)$$

for $n = 2, 3$.

3.6.2 Graduation predictions from alternative assignment rules

The estimated minority graduation rates for the three assignment rules are recorded at the top of Table 3.6, along with the actual graduation rates for the pre-Prop 209 minority UC enrollees. As noted above, we used the characteristics of the latter group of minorities to generate the predictions associated with each of the assignment rules to facilitate comparisons. For both the observed rates and those predicted under each of the three assignment rules, we display the (overall) mean graduation rate and those for the deciles of the minority academic index distribution. To better gauge the predicted changes in graduation rates relative to the pre-Prop 209 ones, we present, in rows (A), (B) and (C) of Table 3.6, the differences between the predicted graduation rates and the pre-Prop 209 observed rates. Below the labeled rows in this table, we express these differences as a percentage of the observed minority graduation rates and, where appropriate, as a percent of the difference between the predicted rates for AR1 and the actual ones.

The average maximum possible improvement in minority graduation rates through matching under AR1 is 4.7 percentage points, which is a 7.5% improvement over pre-Prop 209 minority graduation rates. This average masks more sizeable predicted gains across the distribution of minority academic preparedness. In particular, minorities in the bottom half of the academic index distribution would experience an improvement in graduation rates of almost 10% if students were re-allocated according to AR1. At the same time, the sizes of these gains suggest there are limits to what can be achieved via better matching, an issue to which we return below.

In row (B) of Table 3.6 we display the changes in minority graduation rates that would have occurred if the pre-Prop 209 cohorts of UC enrollees would have sorted themselves across the UC campuses in the manner that minorities did after Prop 209 (AR2). Note that this is a counterfactual evaluation, since we know that the characteristics of the minorities that enrolled within the UC system after Prop 209 did change [Table 3.1]. We find an average improvement of 0.9 percentage point increase in minority graduation rates, a 1.4% improvement over pre-Prop 209 rates. The magnitudes of the gains in minority graduation rates from the re-allocation under AR2 are modest, but higher for the bottom half of the academic preparation distribution, where minority graduation rates would improve by 2.8% (a 1.5 percentage point increase) for those in the second decile. The AR2 allocation achieves 19.3% of the maximum attainable gains associated with AR1 [row (A)]. It achieves more of the maximum possible gains for the bottom part of the preparedness distribution, accounting for up to 27.4% of the possible gains.

Finally, we examine what would have happened to minority graduation rates after Prop 209 was implemented if minorities had been assigned to UC campuses in the same way that whites were. In row (C) of Table 3.6 we present the graduation rates associated with this counterfactual change in assignment rules (AR3). On average, minorities would have done better under AR3 than under AR2, although

the difference in the average graduation rates is only 0.3 percentage points. Under the white post-Prop 209 assignment rules, minorities would have attained over 26% of the maximum possible gain from re-allocation of students across campuses. Moreover, under the white assignment rules, the gains in graduation rates would have been especially large for those at the bottom of the distribution, achieving up to 39.3% of the maximum possible gains.

3.6.3 Alternative assignment rules and school-specific minority representation

We now turn to how these alternative assignment rules would affect the distribution of minority students across universities. First, we consider what the re-allocation of minority students across the UC campuses under AR1 would look like and how big a change it would be relative to the pre-Prop 209 distribution. In Table 3.7 we present tabulations of the shares of minorities that would be assigned to each of the eight UC campuses under the three assignment rules, as well as the actual shares of minorities that enrolled at these campuses prior to Prop 209. Prior to Prop 209 minorities were disproportionately enrolled at the more-selective UC campuses. Almost one-half of minorities were at the three most selective campuses, UC Berkeley, UCLA and UC San Diego, with UC Berkeley and UCLA having the two largest shares. At the same time, UC Santa Barbara had a sizable share (14.3%) of the minorities enrolled in the UC system prior to Prop 209. Under AR1, the allocation of minorities would change dramatically [columns under (A)]. In particular, almost 70% of them would be enrolled at UC Santa Barbara, with the remaining 23.8%, 7.8%, and 0.6% enrolling at UC Riverside, UCLA, and UC Santa Cruz respectively. *No* minorities would enroll at any of the other campuses. Recall that UC Santa Barbara appeared to have an absolute advantage in converting minority enrollments into graduations for most students.

Table 3.6: Minority Graduation Rates within UC System by Academic Preparation, Pre-Prop 209 & under Alternative Post-Prop 209 Campus Assignment Rules[†]

Assignment Rule		Overall Mean	Deciles of Minority Academic Index Distribution									
Pre-Prop 209 Minority (Predicted)		1	2	3	4	5	6	7	8	9	10	
ARI: Maximize Grad. Rates Rule		0.625	0.510	0.548	0.572	0.594	0.617	0.635	0.659	0.683	0.718	
AR1: Maximize Grad. Rates Rule		0.671	0.562	0.603	0.626	0.649	0.669	0.685	0.704	0.721	0.747	
AR2: Post-Prop 209 Minority Rule		0.634	0.523	0.563	0.586	0.607	0.626	0.642	0.664	0.686	0.719	
AR3: Post-Prop 209 White Rule		0.637	0.527	0.570	0.592	0.613	0.631	0.646	0.667	0.687	0.719	
(A)	Maximum – Pre Minority (Pred.)	0.047	0.051	0.055	0.054	0.055	0.052	0.049	0.045	0.039	0.031	
	% of Pre Minority (Pred.)	7.5%	10.0%	10.0%	9.5%	9.3%	8.4%	7.7%	6.9%	4.1%	4.1%	
(B)	Post (Minority) – Pre Minority (Pred.)	0.009	0.013	0.015	0.014	0.013	0.009	0.007	0.006	0.003	0.002	
	% of Pre Minority (Pred.)	1.4%	2.5%	2.8%	2.5%	2.2%	1.4%	1.1%	0.8%	0.5%	0.2%	
(C)	% of [Max – Pre Minority]	19.3%	24.5%	27.4%	26.1%	23.3%	17.0%	14.5%	12.4%	9.0%	6.1%	
	Post (White) – Pre Minority (Pred.)	0.012	0.016	0.022	0.021	0.019	0.014	0.011	0.008	0.004	0.001	
	% of Pre Minority (Pred.)	2.0%	3.2%	3.9%	3.6%	3.2%	2.2%	1.7%	1.2%	0.6%	0.2%	
	% of [Max – Pre Minority]	26.5%	31.9%	39.3%	37.9%	34.2%	26.7%	22.6%	17.9%	11.3%	3.8%	

Data Source: UCOP.

[†] See text for description of how the predicted graduation rates were formed for each of the three assignment rules, AR1, AR2, AR3.

A look at the two columns under (B) of Table 3.7 shows how AR2 re-allocated students across the UC campuses. While obviously less dramatic than the re-allocation associated with AR1, we predict that the pre-Prop 209 UC enrollees would have been reallocated from the three most-selective UC campuses (UC Berkeley, UCLA and UC San Diego) to the less-selective ones (UC Riverside and UC Santa Cruz). In contrast to the re-allocation under AR1, only a modest share of the minorities would be re-allocated to UC Santa Barbara under AR2, the UC campus that we found had an absolute advantage for graduating most minority students.

Comparing the AR3 re-allocation in the columns under (C) of Table 3.7 with those for AR2 in the columns under (B), we see that the post-Prop 209 assignment rule for whites even more dramatically moved students out of the most-selective campuses than did AR2 and, importantly, re-allocated many more of them to UC Santa Barbara, the most productive campus for producing graduation rates for students of most levels of academic preparation.²³

3.7 Decomposing the Effects of Proposition 209 on Minority Graduation Rates

Having examined the role matching played in the higher graduation rates post-Prop 209, we summarize our findings by decomposing the effects Prop 209 had on graduation into three parts. First, as discussed in the previous section, is the effects on matching. Second, is the effect that we term “university response,” the estimated effect of enrolling in the post-Prop 209 period beyond the due to matching and selection. Finally, is the part due to Prop 209 resulting in a better set of minority student attending college.

Table 3.8 breaks out the various mechanisms behind the increased graduation

²³ As we noted earlier, Prop 209 does not require that minority and non-minorities have the same *enrollment* rules. Our analysis does not imply that any of the UC campuses circumvented Prop 209 in their admissions procedures. For example, it is possible that there are racial and ethnic differences in geographical preferences for colleges or in information about graduation probabilities.

Table 3.7: Distribution of Minority Enrollees across UC Campuses, Pre-Prop 209 & Predicted under Alternative Post-Prop 209 Assignment Rules[†]

Campus	(A)				(B)				(C)			
	AR1 –		AR2 –		AR2 –		AR3 –		AR3 –		AR3 –	
	Pre Min. (Pred.)	Max Grad Rate	AR1: Post Min.	AR2: Post White	AR3: Post White	Pre Min (Pred.) % of Pred.	Pre Min (Pred.) % of Pred.	Pre Min (Pred.) % of Pred.	Pre Min (Pred.) % of Pred.	Pre Min (Pred.) % of Pred.	Pre Min (Pred.) % of Pred.	Pre Min (Pred.) % of Pred.
UC Berkeley	0.178	0.000	0.100	0.100	0.041	-0.178	-100%	-0.078	-44%	-0.137	-77%	-77%
UCLA	0.217	0.078	0.140	0.140	0.083	-0.139	-64%	-0.077	-36%	-0.134	-62%	-62%
UC San Diego	0.084	0.000	0.072	0.072	0.069	-0.084	-100%	-0.012	-15%	-0.016	-19%	-19%
UC Irvine	0.087	0.000	0.113	0.113	0.118	-0.087	-100%	0.026	30%	0.031	35%	35%
UC Davis	0.118	0.000	0.127	0.127	0.164	-0.118	-100%	0.009	8%	0.046	39%	39%
UC Santa Barbara	0.144	0.679	0.152	0.152	0.194	0.535	372%	0.008	6%	0.050	35%	35%
UC Santa Cruz	0.077	0.006	0.107	0.107	0.189	-0.072	-93%	0.029	38%	0.112	144%	144%
UC Riverside	0.095	0.238	0.190	0.190	0.143	0.143	151%	0.096	101%	0.048	51%	51%

Data Source: UCOP.

[†] See text for description of how the assignment probabilities for each of the three assignment rules, AR1, AR2, AR3, were determined.

Table 3.8: Decomposing the Effect of Proposition 209 on Graduation[†]

	Method 1		Method 2	
	Level	Share of Total	Level	Share of Total
<i>Total increase</i> = 4.4%				
(a) Improved Matching	0.9%	20.5%	0.9%	20.5%
(b) University Response	2.0%	45.5%	1.3%	29.5%
(c) Selection	1.5%	34.0%	2.2%	50.0%

[†] Selection effect calculated as *Total Increase* − (a) − (b).

rates post-Prop 209. Recall from Table 3.1 that the overall graduation rate increased by 4.4 percentage points for minority enrollees. Of this increase, 20.5% can be explained by better matching of students to the UC campuses based on the students' preparation and campus graduation production functions. Recall that the university response is measured by $\ddot{\phi}_2^*$, the coefficient on *POST* in equation (3.5). We estimated this effect under two scenarios (Methods 1 and 2) that are likely to bound the true effect. The first, Method 1, assumes that the distribution of unobservables for enrollees in the same in the pre- and post-Prop 209 periods, while the second, Method 2, removed pre-Prop 209 minority enrollees with the lowest levels of academic preparation to be more comparable with the better prepared post-Prop 209 minority enrollees. Our estimates imply that this university response accounts for between 29.5% and 45.5% of the graduation rate increase, depending on the Method used. It follows that the remainder of the increase in graduation rates is due to changes the selectivity in the academic preparation and backgrounds of minorities that enrolled after Prop 209. We find that this change in selectivity accounts for between 34% and 50% of the graduation rate increase.

3.8 Conclusion

In this paper we have examined how the match between the student and the school affects college graduation rates. We have found evidence that less-selective UC schools tend to be better at graduating less-prepared students, with more selective

schools better at graduating more-prepared students. These results are relevant to the debate over the merits of affirmative action in university admissions to the extent that affirmative action leads to inefficient sorting.

Using data before and after an affirmative action ban, we found evidence that Prop 209 did lead to a more efficient sorting of minority students within the UC system. However, the effects were relatively small and we can say little about what happened to those that did not attend a UC school as a result of Prop 209.²⁴ Given large differences in academic preparation due to differences in the family backgrounds of students and the quality of the primary and secondary schools they attended, there is little scope for dramatic shifts in graduation outcomes by re-sorting of students across campuses.²⁵ That being said, our results indicate that better matching of students to campuses based on academic preparation does produce the largest graduation rate gains for those students in the bottom part of the distribution of academic preparation. Further, while matching effects are small when comparing five-year graduation rates, a companion paper (Arcidiacono, Aucejo, and Hotz, 2012) shows that mismatch effects are much larger when looking at persistence in STEM fields and in time to graduation.

Possibly our most intriguing finding is that the imposition of an affirmative action ban may have induced a response by universities in their efforts to keep students from dropping out and completing their studies. Previous studies of affirmative action have ignored the potential for such an institutional response targeted at those minorities that do enroll after a ban and our results suggest that the magnitude of the potential detrimental effects of affirmative action bans may be overstated by not taking these

²⁴ While estimates suggest selective schools see a drop in minority enrollment following affirmative action bans (Long 2004 and Hinrichs 2012), overall college enrollment rates remain relatively unaffected following a ban (Backes 2012 and Hinrichs 2012).

²⁵ These results are consistent with Arcidiacono and Koedel (2012) who find that most of the black/white differences in college graduation rates stem from differences in student academic preparation.

responses into account.

More generally, finding ways to improve the college graduation rates of minorities – regardless of the motivation – would appear to be of growing importance, given the evidence that attending but not graduating from college has sizeable consequences in one’s later life. Consider, for example, the disparity in labor market earnings between those who attend but do not graduate from college and those that do graduate. Based on data from the 2008-2010 waves of the American Community Survey (ACS), we estimate that the annual earnings of African American men who completed their BA degree is 47.1% higher than for those who attended but did not graduate from college. The corresponding differentials are even larger for African American women (51.1%) and sizeable for both Hispanic men (36.1%) and women (41.1%).²⁶

²⁶ By way of comparison, the corresponding differentials are 46.5% for white men and 43.0% for white women.

Appendix A

State-Level Descriptive Tables

Table A.1: Whether Individual Lives in Home State

Age Range	<HS Grad	HS Grad	Some Coll	Coll Grad	Overall
18-23	93.9%	92.7%	91.9%	91.4%	92.3%
24-29	93.7%	87.5%	83.4%	70.4%	82.5%
30-35	90.1%	90.0%	81.9%	58.6%	78.6%

Data Source: Author's Calculations, PSID.

Table A.2: Annual Interstate Move Rates

Age Range	<HS Grad	HS Grad	Some Coll	Coll Grad	Overall
18-23	3.1%	3.9%	4.1%	5.2%	4.1%
24-29	3.9%	4.0%	5.1%	9.8%	5.9%
30-35	2.1%	3.1%	2.8%	7.2%	4.2%

Data Source: Author's Calculations, PSID.

Table A.3: Interstate Moves by Age 30

Proportion of Individuals Moving Between 18-30					
	< HS Grad	HS Grad	Some Coll	Coll Grad	Overall
% Moved	15.8%	19.2%	22.3%	37.1%	25.2%
Number of Moves (If Any Moves by 30)					
	< HS Grad	HS Grad	Some Coll	Coll Grad	Overall
One	57.9%	31.0%	36.8%	36.3%	36.3%
Two	26.3%	42.5%	47.4%	29.3%	36.6%
Three or More	15.8%	26.4%	15.8%	34.4%	27.1%
Data Source: Author's Calculations, PSID.					

Table A.4: Wage Regression Coefficients, State Level

Wage Regression Coefficients: Dependent Var Ln(Wage)				
	HS Grad		Coll Grad	
Model 1 (3.4):				
Father's State	0.0128		-0.1746	***
Model 2 (3.5):				
Father's State	-0.0233		-0.1936	***
Cognitive	0.2188	***	0.6411	***
Motor	0.0659		0.0058	
Model 3 (3.6):				
Father's State	-0.0035		-0.1533	***
Cognitive	0.1927	***	0.6288	***
Motor	0.0276		0.0013	
Father's Cog	0.1895	***	0.153	**
Father's Mot	0.008		0.0626	
Model 4 (3.6):				
Father's State	0.1607		-0.6643	***
Cognitive	0.1885	***	0.6056	***
Motor	0.0285		-0.001	
Father's Cog x Diff Loc	0.1543		-0.1457	
Father's Cog x Same Loc	0.1917	***	0.3693	***
Father's Mot x Diff Loc	0.2709	**	-0.1297	
Father's Mot x Same Loc	-0.0382		0.1777	***
Model 5 (3.6):				
Father's State	0.2153	*	-0.8738	***
Cognitive	0.1873	***	0.6213	***
Motor	0.0324		0.0376	
Father's Cog x Diff Loc	0.1289		-0.2673	**
Father's Cog x Same Loc	0.1921	***	0.3798	***
Father's Mot x Diff Loc	0.2501	*	-0.1212	
Father's Mot x Same Loc	-0.0412		0.1715	**
Occ. Distance x Diff Loc	0.1758		-0.2888	***
Occ. Distance x Same Loc	-0.0071		0.042	

"Same/Diff as Father" Location are at the level of US State

*, **, *** indicate significance at 10%, 5%, 1% levels

Data Source: Author's Calculations, PSID.

Appendix B

UCOP Individual Summary Statistics and Baseline Model Estimates

B.1 Appendix

Table B.1: Characteristics of UC Applicants, Admits, and Enrollees Pre-Prop 209 and Post-Prop 209 Change, Asian Americans and Others[†]

	Applied		Admitted		Enrolled		Graduated	
	Pre-Prop 209	Change	Pre-Prop 209	Change	Pre-Prop 209	Change	Pre-Prop 209	Change
<i>Asians:</i>								
No. of Asians	53,739	9,629	42,556	6,412	26,130	4,316	19,337	4,265
High School Acad. Index	701.9	8.2***	723.7	5.4***	717.2	9.8***	729.6	8.3***
Parents have BA	0.652	0.004	0.659	-0.007**	0.636	-0.002	0.656	-0.008*
Parents' Income \leq \$30K	0.293	-0.026***	0.301	-0.022***	0.322	-0.028***	0.301	-0.027***
Parents' Income \geq \$80K	0.291	0.053***	0.288	0.046***	0.266	0.052***	0.280	0.054***
Graduation Rate							0.749	0.037***
<i>Others, including Unknowns:</i>								
No. of Others	10,143	12,161	8,231	8,810	4,129	4,693	3,081	3,622
High School Acad. Index	719.3	-2.6**	741.3	-2.8**	731.2	2.0	741.6	1.1
Parents have BA	0.745	0.018***	0.765	0.010	0.751	0.010	0.769	0.009
Parents' Income \leq \$30K	0.195	-0.013**	0.186	-0.008	0.203	-0.010	0.184	-0.004
Parents' Income \geq \$80K	0.402	0.044***	0.413	0.034***	0.384	0.047***	0.409	0.040***
Graduation Rate							0.741	0.015*

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Data Source: UCOP individual data, Pre-Prop 209 (1995-97); Post-Prop 209 (1998-2000).

Variables: *No. of Observations* is the total number of students who engaged in activity indicated in column heading; *No. of Obs./No. of HS Grads* is ratio of a column's No. of Observations to the number of public high school graduates per year in California; *Graduation Rate* is share of enrolled students that graduated in 5 years or less; *High School Acad. Index* is sum of re-scaled student's SAT I score (0 to 600 scale) plus re-scaled student's UC-adjusted high school GPA (0 to 400 scale); *Parents have BA* is indicator variable of whether student has at least one parent with Bachelor Degree or more; *Parents' Income \leq \$30K* is indicator variable for whether parents' annual income is \leq \$30,000, where Pre-Prop 209 income are inflation-adjusted to Post-Prop 209 levels; *Parents' Income \geq \$80K* is corresponding variable whether parents' annual income is \geq \$80,000; and where *Graduated* denotes those who graduated in 5 years or less.

Table B.2: Estimates Using the Baseline Method for Under-Represented Minorities, Whites and Asian Americans

	URM	White	Asian Amer.
<i>POST</i>	0.040*** (0.006)	0.023*** (0.004)	0.032*** (0.004)
UC Berkeley	-0.405*** (0.086)	-0.003 (0.089)	-0.095 (0.073)
UCLA	-0.547*** (0.089)	-0.044 (0.089)	-0.078 (0.077)
UC San Diego	-0.291** (0.123)	0.320*** (0.100)	-0.061 (0.081)
UC Davis	-0.553*** (0.093)	0.189** (0.086)	-0.142** (0.069)
UC Irvine	-0.198* (0.104)	0.043 (0.094)	-0.089 (0.067)
UC Santa Barbara	-0.136 (0.090)	0.286*** (0.083)	-0.113 (0.086)
UC Santa Cruz	0.010 (0.093)	0.479*** (0.086)	0.240*** (0.093)
Acad. Index	0.327*** (0.103)	0.693*** (0.101)	0.551*** (0.075)
UC Berkeley \times Acad. Index	0.538*** (0.129)	0.053 (0.118)	0.194** (0.096)
UCLA \times Acad. Index	0.766*** (0.133)	0.119 (0.120)	0.165 (0.102)
UC San Diego \times Acad. Index	0.413** (0.178)	-0.349*** (0.134)	0.160 (0.110)
UC Davis \times Acad. Index	0.722*** (0.144)	-0.174 (0.118)	0.290*** (0.098)
UC Irvine \times Acad. Index	0.282* (0.162)	-0.022 (0.131)	0.179* (0.095)
UC Santa Barbara \times Acad. Index	0.236* (0.142)	-0.289** (0.115)	0.224* (0.126)
UC Santa Cruz \times Acad. Index	-0.024 (0.149)	-0.628*** (0.121)	-0.276* (0.142)
Admitted to UC Berkeley	0.027** (0.013)	-0.002 (0.009)	0.022** (0.009)
Admitted to UCLA or higher ranked	0.003 (0.017)	0.030*** (0.009)	0.029*** (0.010)
Admitted to UC San Diego or higher ranked	0.005 (0.017)	0.039*** (0.009)	0.014 (0.009)
Admitted to UC Davis or higher ranked	0.058*** (0.017)	0.032*** (0.008)	0.013 (0.014)
Admitted to UC Irvine or higher ranked	0.004 (0.016)	-0.013 (0.009)	0.018** (0.009)
Admitted to UC Santa Barbara or higher ranked	-0.001 (0.021)	0.024** (0.011)	0.044*** (0.017)
Admitted to UC Santa Cruz or higher ranked	0.048** (0.022)	0.000 (0.019)	-0.027* (0.016)
Initial Major Soc. Sci.	0.027*** (0.008)	0.011** (0.005)	0.031*** (0.006)
Initial Major Science	-0.083*** (0.007)	-0.050*** (0.004)	-0.047*** (0.004)
Constant	0.443*** (0.063)	0.186*** (0.067)	0.294*** (0.047)
Family Background Characteristics	Yes	Yes	Yes
Adjusted R^2	0.045	0.046	0.061

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.
Coefficient standard error in parentheses.
UC-Riverside is the omitted UC campus in these regressions.

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Biography

Patrick Coate was born on September 9, 1985, in Baltimore, MD. He graduated *summa cum laude* from the University of Dayton in 2007 with a B.S. in Mathematics with a second major in Economics.

Patrick then entered graduate study at Duke, where he earned an M.A. in 2008. He will complete his Ph.D. in July 2013 and begin work as a Postdoctoral Research Fellow at the University of Michigan Population Studies Center in Fall 2013.